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State – Level Regulation's Effectiveness in Addressing Global Climate Change and Promoting Solar Energy Deployment

By

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Abstract

Paper 1, Local Solutions to Global Problems: Climate Change Policies and Regulatory Jurisdiction, considers the efficacy of various types of environmental regulations when they are applied locally to pollutants whose damages extend beyond the jurisdiction of the local regulators. Local regulations of a global pollutant may be ineffective if producers and consumers can avoid them by transacting outside the reach of the local regulator. In many cases, this may involve the physical relocation of the economic activity, a problem often referred to as "leakage." This paper highlights another way in which local policies can be circumvented: through the shuffling of who buys from whom. The paper maintains that the problems of reshuffling are exacerbated when the options for compliance with the regulations are more flexible. Numerical analyses is presented demonstrating that several proposed policies to limit greenhouse gas emissions from the California electricity sector may have very little effect on carbon emissions if they are applied only within that state. Paper 1 concludes that although local subsidies for energy efficiency, renewable electricity, and transportation biofuels constitute attempts to pick technology winners, they may be the only mechanisms that local jurisdictions, acting alone, have at their disposal to address climate change.

Paper 2, Pass-Through of Solar PV Incentives to Consumers: The Early Years of California's Solar PV Incentives, examines the pass through of incentives to California solar PV system owners. The full post-subsidy price consumers pay for solar power is a key metric of the success of solar PV incentive programs and of overall PV market performance. This study examines the early years of California's most recent wave of distributed solar PV incentives (2000-2008) to determine the pass-through of incentives. Examination of this period is both intellectually and pragmatically important due to the high level of incentives provided and subsequent high cost to ratepayers; policymakers' expectations that price declines accrue to consumers; and market structure characteristics that might contribute to incomplete pass-through. This analysis shows that incentive pass-through in the California residential solar PV programs was incomplete. Consumer prices declined 54 cents for every additional dollar of incentive received. A large share of the incentive is captured by the solar PV contractor or other actors in the solar PV supply chain. The finding of incomplete pass-through is persistent across specifications. The analysis also identifies a lower degree of incentive pass-through for consumers in the highest income zip codes. Whether expectations of incentives' pass-through align with reality is critically important in the beginning years of emerging clean energy technology programs since this can affect the likelihood of future government investments and public support. Given the often-held policy assumption that consumer prices are declining in response to incentives, it is useful for policymakers to understand the circumstances under which such an assumption may not hold.

Paper 3, Testing the Boundaries of the Solar Photovoltaic Learning System, tests how the choice of experience curves' geographic and technology assumptions affect solar PV experience curve results. Historically, solar PV experience curves have assumed one experience curve represents both module and non-module learning and that this learning happens at a global scale. These assumptions may be inaccurate for solar PV since the learning system, and technology and geographic boundaries, are likely different between PV modules and non-module components. Using 2004 to 2008 PV system price data

from 13 states, and a longer time series of PV price data for California, some evidence is found that cumulative capacity at the state level is a better predictor of non-module costs than U.S. or global capacity. This paper explores, but is unable to significantly determine, how knowledge spillovers from neighboring states can influence a state's non-module costs. Given data limitations, and limitations to the two-factor experience model methodology itself, it is not possible to conclusively determine the correct geographic boundary for the non-module learning system. Throughout the paper ways in which the experience curve model and data can be augmented to achieve a better estimation are discussed.

Dedication

I dedicate this dissertation to Professor Severin Borenstein, my mother Professor Phylis Peterman, and my husband Matt Lesenyie who all kindly, and persistently, encouraged me to finish this thesis as I pursued career and family.

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Introduction

Human induced climate change presents a significant, and potentially catastrophic, environmental and health problem for policymakers to address. The Intergovernmental Panel on Climate Change concludes that in order to keep global warming under the 3.6 degrees Fahrenheit warming threshold agreed to in the 2015 Paris Agreement, global greenhouse gases must be 40 to 70% lower by 2050 compared to 2010 and emissions level near zero or below by 2100.[1] Not only is the magnitude of the problem great, but its solutions are complicated given the variety of warming sources, the long life of greenhouse gases and polluting assets, the uneven distribution of causes and benefits, and the near term high costs of action.

Given that the electricity and transportation sectors represent 25% and 14% of global greenhouse gas emissions respectively, greenhouse gas reductions in these sectors will be critical.[2] In the United States, these sectors will be required to achieve even greater transformation since they represent 30% and 26% of U.S. greenhouse gases respectively.[3] Primary mitigation strategies for these sectors include reducing energy consumption and a massive shift towards lower carbon fuels such as solar, wind, and bioenergy.

The 2015 Paris Agreement represents progress and is the first global climate change treaty including commitments from both the affluent United States and European Union and industrializing China and India. The treaty provides direction regarding specific greenhouse gases reduction targets, timing for reducing emissions, financing, and emissions accounting and reporting. However, given the necessarily high-level nature of the 195 nation commitment, specific policy interventions continue to be implemented at the national and sub-national level.

The United States, the largest emitter of greenhouse gases over time, notably has lacked federal climate change and renewable energy policies, resulting in individual states and cities forging ahead with local greenhouse gas reduction strategies. Recent efforts by the U.S. Environmental Protection Agency to promulgate the Clean Power Plan, the nation's first federal limit on power plant greenhouse gases, have been stayed by the U.S. Supreme Court pending consideration of a multi-state lawsuit against the plan.

In recent decades, states concerned with climate change such as California, Hawaii, and New York, have instituted state level greenhouse gas goals and clean energy programs. Some prominent program examples include California's greenhouse gas targets, the Northeast cap-and-trade program, and Hawaii's renewable standards. In 2006, California adopted the first binding state greenhouse gas target, Assembly bill AB32, which set a target of 1990 levels of greenhouse gases by 2020 and 80% below 1990

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[1] IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland, 151 pp.

[2] Ibid.

[3] Environmental Protection Agency. (2016). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2014. (April 2016).

levels by 2050. This target was increased in 2015 to include an interim 2030 target of greenhouse gases 40% below 1990 levels by 2030. In 2009, a consortium of northeastern states developed the Regional Greenhouse Gas Initiative, the first U.S. mandatory market-based program to reduce greenhouse gas emissions. In 2015, Hawaii promulgated a 100% by 2045 renewable portfolio standard.

A number of questions arise when considering the consequences of state level regulation to address a global problem such as climate change. How to impose binding regulations on sectors such as electricity and transportation that operate regionally, if not globally? What regulatory mechanisms, including restrictions and subsidies, are most appropriate for ensuring actual reductions? How does a state ensure the benefits of its clean technology investments lead to lower costs solutions and benefits within and beyond its borders?

This dissertation, in three papers, tackles some of these questions, with a particular focus on California policy and regulations implemented in the 2000s. This period represents the beginning of California's recent wave of aggressive efforts to address climate change, including the introduction of statewide renewable energy programs.

The first paper, "Local Solutions to Global Problems: Climate Change Policies and Regulatory Jurisdiction," co-authored with Professor James Bushnell and Professor Catherine Wolfram, considers the efficacy of various types of environmental regulations when they are applied locally to pollutants whose damages extend beyond the jurisdiction of the local regulator. The paper discusses various regulatory tools, specifically those that impose costs on the polluting entities and those that subsidize "clean" behavior or technologies.

We discuss the vulnerability of these regulatory tools to the issues of leakage and reshuffling, using specific examples of state level electricity sector climate change initiatives in the United States. We also present numerical analyses demonstrating that several proposed policies to limit greenhouse gas emissions from the California electricity sector may have very little effect on carbon emissions if they are applied only within that state because producers and consumers can avoid these policies by transacting outside the reach of the local regulator. One interesting finding is that if a jurisdiction is large enough, a local standard may force an industry beyond a tipping point, where it is less costly to produce all goods, even those sold outside the regulated region, to comply with the local standard. In this case, the local standard, far from being bypassed, actually gets leveraged onto other regions. A second interesting finding is that the promotion of clean technologies through direct subsidies may be one of the most effective ways local jurisdictions can address environmental goals. Although subsidies are some of the least attractive regulatory tools from an economic efficiency perspective they can have a measurable impact on pollution.

As the first paper notes, proponents of subsidies often point to a variant of the "infant industries" argument. This hypothesis, often applied in the context of international trade, argues that certain technologies or industries would be very competitive with incumbent technologies if they could capture the necessary economies of scale or learning. Thus, the theory is that the subsidies promoting these technologies speed up their development, moving the industry along the learning curve faster, or allowing it to grow to a minimum efficient scale more quickly. Once these technologies reap the benefits of such efficiencies, no further intervention is necessary. These new technologies will, in theory, continue to be preferred even if the environmental costs of the old technologies are not borne by the producers.

Although a plausible theory, designing accurate incentives to best capture possible appropriable learning is tricky. Perhaps the biggest drawbacks of targeted subsidies are the practical barriers to implementing them effectively. Even with skilled and dedicated regulators, the information required to pick the "right" technologies is daunting. There is considerable risk that large subsidies will go to technologies that would not prove competitive under ideal regulations. Politicians and regulators are in effect placing large bets that the expected economies of scale and learning will in fact materialize.

My second paper, "Pass Through of Solar PV Incentives to Consumers: The Early Years of California's Solar PV Incentives," examines one of the economic factors important to consider when establishing subsidy programs: incidence, i.e. how much of an incentive actually flow through to customers. Subsidy incidence "falls" on the group (sellers vs. buyers) that receives the benefit of the subsidy. A subsidy can be passed forward to the consumer or backwards to the supplier. Pass-through to either of these groups can be full, e.g. 100 percent of the subsidy or incomplete, e.g. less than 100 percent. However the statutory burden of the subsidy is not necessarily the same as the economic burden. Whether consumers or suppliers legally receive the subsidy is irrelevant to the distribution of the subsidy benefits. Incidence depends on the relative elasticities, i.e., price responsiveness, of supply and demand. Parties with more inelastic supply or demand benefit from the subsidies (or bear the greatest tax burden). Given that the post-subsidy price consumers pay for solar power is a key metric of the success of solar PV incentive programs and overall PV market transformation, understanding the degree of incidence, and factors that result in incomplete pass through, is important for policymakers.

California has allocated billions of dollars to its solar PV incentive programs. Paper 2 focuses on solar incentive programs from 1998-2008 because this period was characterized by a plethora of high incentives. In addition, market structure characteristics that might contribute to incomplete pass-through, such as reduced information transparency and imperfect competition, were more likely present in this period. Whether expectations of incentives' pass-through align with reality is critically important in the beginning years of emerging clean energy technology programs since this can affect the likelihood of future government investments and public support. Given the often-held policy assumption that consumer prices are declining in response to incentives, it is useful for policymakers to understand the circumstances under which such an assumption may not hold. This analytical framework is not only relevant for emerging solar PV programs but for assessing the wave of new clean energy technologies such as energy storage and electric vehicles.

Using a partial equilibrium model and incentive and PV system data from the major California solar PV incentive programs, Paper 2 shows that incentive pass-through in the California residential solar PV programs is incomplete. Consumer prices decline 54 cents for every additional dollar of incentive received. In other words, 46 cents of every dollar of consumer side incentive is captured by the supply side. The analysis also identifies a lower degree of incentive pass-through for consumers in the highest income zip codes, which could be due to a variety of factors including these consumers being less price sensitive or engaging in less search activity.

Findings of incomplete incentive pass-through have a number of policy design and evaluation implications. If the aim of incentives is to reduce costs to consumers, incomplete pass-through mutes the expected price signal and may increase the time necessary to reach capacity deployment goals. This analysis finds that a large share of the incentive is captured by the solar PV contractor or other actors in the solar PV supply chain. However, this is not necessarily a bad outcome for ratepayers providing the incentive. For example, if installers utilize the rents they capture to increase marketing and outreach and grow the PV market this may be beneficial for ratepayers. However, alternatively, if installers are focused on competing for rents from the existing solar PV customer base and dissipating rents through customer acquisition and defensive advertising, this does not support ratepayer and policy goals. As affirmed in Papers 1 and 2, the effectiveness of regulatory tools depends on the extent of jurisdiction and market conditions. As such, not all tools will be equally effective, at all times, for different jurisdictions. Even with more direct subsidies, there are various factors that may hinder success. As Paper 2 details, when considering clean energy subsidies, policymakers should pay careful attention to what their expectations are regarding who ultimately receives the subsidy and the market conditions that most lead to that outcome. In particular, policymakers should be aware of any market barriers that might limit competition and supply elasticity, such as licensure requirements. Such a condition can lead to lower pass through of incentives to end use consumers.

As noted, Paper 1 and Paper 2 acknowledge that a key motivation for introducing incentives is the belief that endogenous learning exists in infant clean energy industries, i.e. cumulative experience with a technology will lead to cost declines and industry growth. It is often assumed that subsidies are useful tools for jumpstarting this learning. Energy modelers and policymakers use forecasts of possible learning, derived from clean technology industry experience curve models, to determine appropriate subsidy levels. My third paper, "Testing the Boundaries of the Solar Photovoltaic Learning System," delves into how experience curve models are developed and some important considerations with their development to ensure better forecasting certainty.

Experience curves model how technology costs decline is relation to the cumulative installed capacity of a technology. The simplicity of inputs required to create an experience curve – a time series of technology costs, initial starting capacity, and cumulative installed capacity – have led to its regular use. However this simplicity has also led to critiques of such models' broader, applicability and validity. Paper 3 tests how the choice of experience curves' geographic and technology assumptions affect solar PV experience curve results. Historically, solar PV experience curves have assumed one experience curve represents both module and non-module learning and that this learning happens at a global scale. These assumptions may be inaccurate for solar PV since the learning system, and technology and geographic boundaries, are likely different between PV modules and non-module components. The majority of PV experience curves have focused on the module cost declines. However, the share of total PV system cost represented by the module component has declined over time, especially in smaller PV systems.

Using 2004 to 2008 PV system price data from 13 states, and a longer time series of PV price data for California, paper 3 finds some evidence that cumulative capacity at the state level is a better predictor of non-module costs than U.S. or global capacity. However, given the collinearity of inputs and the small sample size, these findings are not conclusive. To test this and alternative hypotheses, the paper estimates experience rates using reduced form regression analysis. Empirical tests for non-nested models are used to compare the state, national, and global models.

Paper 1 notes that even the presence of a strong potential for learning or scale economies does not necessarily cause a market failure. The key issue is whether those economies can be appropriated, through patents or a dominant position in the market, or whether there are significant knowledge "spillovers." If a firm can profit from developing a new technology there is a market incentive to innovate. If the innovations are easily copied by competitors, investment in research and development becomes a public good, thereby justifying public support. The traditional experience models assume no knowledge spillovers and that the impact of experience does not decay with distance. Paper 3 explores the potential for knowledge spillovers across states. For non-module costs I hypothesize that spillovers will be positive, but limited since not all knowledge is appropriable by a state. I expect the impact of other state capacity to be greater on a state's non-module costs if the state of interest has a relatively smaller market than neighboring states. However, with this analysis I am unable to significantly determine, how knowledge spillovers from neighboring states influence a state's non-module costs.

Understanding the influence of a geographic boundary on learning has implications for local policymakers. If non-module costs are influenced by city level actions to expand solar PV capacity, a city council may have more motivation to institute local solar PV subsidies or fast track permitting. However, if the local costs are just as easily affected by expanding state level capacity and subsidies, or are a function of global trends, city regulators may focus instead on directing scarce local resources towards other initiatives.

Another key factor that arises when thinking about appropriability is the difference between endogenous learning and economies of scale. Technology learning, such as learning-by-doing, arises from aggregate increases in cumulative production and the development of new production functions. Scale effects, such as economies of scale, result from increased quantity in a given period and a more efficient use of inputs. These effects are often conflated in experience curve studies, but have differing implications for how much impact subsidies aimed at spurring endogenous learning may have.

If economies of scale are a greater price driver than endogenous learning, then there is less argument for government support because those cost reductions are fully appropriable, and hence will be pursued by firms. Moreover, if cost declines are being driven purely by economies of scale, these companies will not see cost declines after they reach a minimum efficiency. In this case, overall incentives designed on a composite learning estimate will underperform and not spur expected market cost declines. Paper 3 attempts to disaggregate scale and learning effects by including proxies for both, however the results in most specifications are not significant. Further research should focus on disaggregating these effects and assessing implications for setting appropriate subsidy levels.

Given the sensitivity of endogenous learning forecasts to model inputs and data quality, Practitioners should exercise great care when employing them to design subsidies in emerging clean energy markets. Such models can be bolstered via the use of sensitivity tests, larger data sets, and more disaggregated modeling techniques. Paper 3 details some of the factors that may reduce the accuracy of experience curve forecasts. In particular, practitioners using experience curve models to forecast solar PV non-module prices should thoroughly consider how the geographic boundary of the market is defined, the relationship between price and cost, the possibly endogenous relationship between prices and capacity, and the quality and time series of data available. Overestimation of the experience rate will underestimate the time needed for solar PV costs to reach parity with fossil generation in a given market. Too low an estimate will underestimate the role of incentives, and cumulative deployment as cost drivers. Both outcomes will have implications for energy policy and renewable incentive program design, technology preferences, and technology roadmaps. This issue is not unique to solar PV, and has implications for all clean energy technology development.

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Local Solutions to Global Problems: Climate Change Policies and Regulatory Jurisdiction [1]

Introduction

This paper considers the efficacy of various types of environmental regulations when they are applied locally to pollutants whose damages extend beyond the jurisdiction of the local regulator. For example, within the United States, many of the efforts to adopt policies to mitigate climate change are taking place at the local level. A number of states (e.g., California, New Jersey, New York, Oregon, Rhode Island), impatient with what is perceived as inadequate federal action, have adopted various controls to address climate change. At the same time, many US cities have adopted climate change policies, as evidenced by the over 700 mayors who have signed the US Conference of Mayors Climate Protection Agreement. Indeed, the growing market for voluntary carbon offsets, purchased by individuals, can be viewed as the ultimate local action. Further, the global nature of the climate change problem means that even actions taken by individual countries can face the same types of problems as those experienced by cities or states.

Unfortunately, local regulations of a global pollutant may be ineffective if producers and consumers can avoid them by transacting outside the reach of the local regulator. In many cases, this may involve the physical relocation of the economic activity, a problem often referred to as "leakage." This paper highlights another way in which local policies can be circumvented: through the shuffling of who buys from whom. Reshuffling is a concern when buyers are subject to regulations (i.e., downstream regulation). While leakage can be costly, as, for instance, when firms relocate their production, with reshuffling, neither the location nor the costs of production need change.

We maintain that the problems of reshuffling are exacerbated when the options for compliance with the regulations are more flexible. The very flexibility that makes market based regulations, such as cap-and-trade, attractive, can also make them susceptible to circumvention if only applied locally. In contrast, where leakage is concerned, the cost impacts of regulation matter more than the flexibility of the mechanism. We argue that leakage problems are more pronounced with regulations that impose a cost on firms than with subsidies designed to reward production from nonpolluting sources.

Ironically, the tools that offer local regulators the greatest potential to make real progress toward an environmental goal may be among the least attractive from an economic efficiency perspective when considering regulation on a large scale. In particular, targeted subsidies for "clean technologies," although vulnerable to political favoritism and limited in flexibility, can have a measurable impact on pollution. Therefore, although local subsidies for energy efficiency, renewable electricity, and transportation biofuels constitute attempts to pick technology winners, they may be the

[1] This paper was published as Bushnell J., Peterman, C. and .Wolfram C. (2008). "Local Solutions to Global Problems: Climate Change Policies and Regulatory Jurisdiction." Review of Environmental Economics and Policy 2(2): 175-193 and is submitted here with permission from co-authors. Some changes to the paper have been made by C. Peterman to reflect policy updates since the paper was published in 2008.

only mechanisms that local jurisdictions, acting alone, have at their disposal to address climate change.

The paper proceeds as follows. The next section discusses various regulatory tools, which we divide into two broad categories: those that impose costs on the polluting entities and those that subsidize "clean" behavior or technologies. In the third section, we discuss the vulnerability of these regulatory tools to the issues of leakage and reshuffling. The fourth section explores in detail the issues of leakage and reshuffling using specific examples of state level climate change initiatives in the United States. We focus particularly on the electricity sector, which has been one of the main targets of early efforts to mitigate climate change, in part because it accounts for more CO2 emissions than any other sector of the US economy. We also present numerical analyses demonstrating that several proposed policies to limit greenhouse gas emissions from the California electricity sector may have very little effect on carbon emissions if they are applied only within that state. The last section summarizes our findings and concludes.

Policy Options

In this section, we describe the broad spectrum of policy options for regulating environmental pollutants and briefly discuss the relative merits of these policies. We distinguish between policies that impose costs on emitters and those that subsidize activities that regulators deem desirable. Of course both types of policies involve a component of revenue redistribution. For example, subsidies to some customers or firms must be paid for by someone, and "costly" regulations such as emissions taxes or cap-and-trade can generate revenue windfalls that can be redistributed in many ways. Later we argue that the different types of regulations have different implications for local jurisdictions.

Cost-imposing regulations

One traditional approach to an environmental problem is to enact policies that cause firms to internalize the negative externalities created by their emissions. This can be achieved using several different regulatory tools, including technology mandates, environmental standards, and market-based regulations. These policies require firms to either take costly mitigation actions or forgo profitable, but polluting, activities. As a result, these regulations all impose an implicit (or explicit) tax on the polluting activities of firms. They can also vary in the flexibility they allow for compliance.

Command and control regulations: technology mandates and standards

We begin by describing the least flexible regulatory tools—technology mandates and environmental standards—which are often referred to as command-and-control regulations. Technology mandates dictate specific technologies (the how of environmental regulations) and the set of firms that must adopt the technologies (the "who" of an environmental improvement strategy). For example, under the New Source

Performance Standards in the US, new plants built in counties that are in attainment with the National Ambient Air Quality Standards must install the Best Available Control Technology (BACT). In practice, the BACT is essentially determined through case-by-case negotiations between the firm and the Environmental Protection Agency.

A slightly more flexible type of command-and-control regulation is an output-based environmental standard, such as a maximum limit on the emission of a pollutant or on the energy usage of an appliance. In some cases, each source of emissions (e.g., a power plant, an appliance) is required to comply with the standard, but it is left to the producer of the polluting product to determine the most cost-effective way to achieve compliance. In other cases, standards are applied over multiple sources, such as a standard on the average emissions across all of a firm's plants. For instance, under the Tier 2 vehicle emissions reduction program in the US, automobile manufacturers must achieve a fleet average emission rate of 0.07 grams of NOx per mile. Subject to this constraint, firms may determine the exact emissions rate for any given vehicle model as well as the particular technology they will use to achieve that rate.

If mandates or standards are enforced broadly, they can be very effective at achieving an environmental goal. So long as the standards are binding, firms and consumers will alter their behavior, for instance, by installing pollution control equipment that they otherwise would not or by purchasing more efficient appliances than they would have. The standards will then result in lower emissions within the jurisdiction where they are imposed. Regulators can determine with minimal monitoring and enforcement costs whether firms are complying with the standards.

In general, command-and-control regulations have been criticized by economists as an inflexible and inefficient approach for dealing with environmental problems. The main criticism of regulatory mandates and standards has been that they are much more costly than necessary, in terms of both the costs to the firms and the foregone consumer welfare of people who would otherwise consume a product that has been banned or made more expensive by the regulatory standard. This is because all firms are required to meet the same standard. If there is heterogeneity across firms, for instance in their production processes or in the vintage of their capital, it may be relatively inexpensive for some firms to achieve substantial emissions reductions, while for others it may be prohibitively costly to achieve any reduction in emissions. In short, one-size fits-all standards do not recognize the potential differences in compliance costs across the regulated sources, and therefore cannot take advantage of these differences. The severity of this problem is obviously closely related to the actual size of those cost differences. Unfortunately, it is often difficult to know exactly how much costs will vary before the regulations are put into place.

Market-based regulations

The most flexible forms of cost-imposing regulations are market-based policies. These include taxes on emissions or programs that allow the government to limit emissions by issuing permits that can be traded among polluters (known as "cap-and-trade"). Rather than dictating the technology (the how) or even the specific emissions of a facility or firm (the who), these programs use price signals to provide incentives to firms to reduce emissions in the most cost-effective way possible.

An emissions tax places an explicit charge on each unit of pollution produced by a firm or individual.[2] If a firm has options for reducing its emissions that are less expensive than the tax itself, then it should adopt those options and reduce its emissions. Importantly, one of the options likely to be considered is simply consuming less of the input that is producing the pollution (e.g., fuel, fertilizer, chemicals). Thus taxes, in a relatively straightforward fashion, can directly and appropriately impact both production and consumption choices in a market.

An alternative market-based policy is a cap-and-trade regulation of pollution quantities.[3] A cap-and-trade system imposes an overall regional limit on total emissions (the cap) but allows flexibility as to which sources within that region actually emit. Emissions permits or credits, totaling no more than the regional cap, are created and allocated to the regulated firms. In theory, firms that can cheaply reduce their emissions will sell credits to firms that find it very expensive to reduce (the trade). The net result is that the emissions target is achieved in a way that minimizes overall costs. Note that regardless of whether a firm is buying or selling permits (and regardless of whether the initial allocation of permits was given or sold to a firm), polluting under a cap-and-trade system entails a marginal cost that is equal to the market price of the permits. In other words, for each additional ton of pollution emitted, net buyers of permits must purchase an additional permit, while net sellers incur a cost equal to the lost opportunity to sell another permit.

Because of their inherent flexibility, these policies are attractive in circumstances in which they can be practically applied. They do not require a perfectly informed regulator to develop the optimal carbon-reducing strategy. In theory, individual firms will arrive at the least cost method for reducing their emissions because, under most circumstances, they have an incentive to do so.[4] Regulators still play a central role in a market-based system, as the parameters they set for the regulatory instruments will drive firms' decisions. However, their role is more limited than under other regulatory approaches.

Subsidy programs

Next we describe policies that attempt to regulate pollutants through the carrot of financial subsidies rather than the stick of emissions limitations. In the policy arena, the promotion of "clean" technologies has been a popular alternative to limitations on the use of "dirty" technologies. The promotion of clean technologies can be accomplished

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[2] Nordhaus (2007) discusses many of the advantages of taxing carbon emissions rather than setting quantity limits through something like a cap-and-trade policy.

[3] 2Dating back to Weitzman (1974), there is a rich literature in environmental economics on the proper use of "price" tools such as emissions taxes vs. "quantity" tools such as command and control regulations or emissions caps. The general idea is that taxes help to limit uncertainty over the costs of compliance while quantity regulations help to limit the uncertainty over how much pollution results.

[4] There are cases where a firm's incentives may not be strictly aligned with minimizing its compliance costs. For example, a regulated utility may prefer options that can be added to its rate base (see Fowlie 2006).

through direct subsidies for the manufacture or installation of the technologies, tax incentives, or mandates that buyers procure a certain percentage of their consumption from clean sources.[5] As with cost-imposing regulations, subsidies can vary in their regulatory flexibility, ranging from an inflexible subsidy on specific technologies to a more market-based approach in which the subsidy increases in proportion to the positive externalities associated with goods.

Consider first an example of a direct subsidy for a particular clean technology. Many states provide refunds to homeowners who install solar photovoltaic cells to produce low emissions electricity. The subsidy can also take the form of a requirement that a certain share of purchases be from low-emissions sources. For instance, California has adopted a low-carbon fuel standard (LCFS), which requires a reduction in the average carbon content of transportation fuels. Several other states are actively considering an LCFS, and there are some proposals for a national low-carbon fuel standard. Here, since the focus is on the mix of transportation fuels sold, rather than on reducing consumption of transportation fuels, an LCFS is largely a subsidy for ethanol and other low-carbon fuels. Which particular low carbon fuels will be used to meet an LCFS will be determined by market competition between the fuel producers.

Proponents of subsidies often point to a variant of the "infant industries" argument. This hypothesis, often applied in the context of international trade, argues that certain technologies or industries would be very competitive with incumbent technologies if they could capture the necessary economies of scale or learning. Thus, the subsidies promoting these technologies speed up their development, moving the industry along the learning curve faster, or allowing it to grow to a minimum efficient scale more quickly. Once these technologies reap the benefits of such efficiencies, no further intervention is necessary. These new technologies will, in theory, continue to be preferred even if the environmental costs of the old technologies are not borne by the producers.

It is important to note that even the presence of a strong potential for learning or scale economies does not necessarily cause a market failure. The key issue is whether those economies can be appropriated, through patents or a dominant position in the market, or whether there are significant knowledge "spillovers." If a firm can profit from developing a new technology, there is a market incentive to innovate. If the innovations are easily copied by competitors, investment in research and development becomes a public good, thereby justifying public support.

There have been several criticisms of "green" subsidies. First, although it is perhaps more politically appealing to make clean technologies cheaper than to make dirty sources more expensive, such an approach sends the wrong message to consumers. Subsidies impose no additional costs on continued consumption from dirty sources. The opportunity for encouraging conservation in the obvious way, by making the production more expensive, is therefore lost. In practice, the cost of direct subsidies is often borne by other customers, which means that at least indirectly; dirty consumption can be made more expensive. Similarly, subsidizing a source that is less bad than the alternative still

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[5] Note that here we are drawing a distinction between mandates or standards imposed on consumers that implicitly subsidize producers using clean technologies, from mandates imposed directly on producers (i.e., the users of dirty technologies), which we discussed in the previous subsection.

promotes consumption of the "bad." For example, in the context of the LCFS, although encouraging a transition from petroleum-based fuels to biofuels can reduce the greenhouse gas (GHG) impact of each mile traveled, the production of biofuels themselves still creates GHGs.[6] Thus, by subsidizing the consumption of biofuels, the policy could actually lead to higher GHG emissions.[7]

A second, related criticism of "green" subsidies is that they will indirectly reduce the prices for dirty products by drawing demand away from them. From a consumer perspective this may sound appealing, but from the perspective of an environmental regulator, lower prices for dirty products are counterproductive. Even if consumption of the disfavored product is discouraged within the region where the subsidies are applied, lower prices will encourage consumption elsewhere.[8] Therefore, when applied locally, even subsidies of alternative energy sources are not immune to spillovers in other regions.

The overall effect of a local subsidy will be a function of the relative price impacts of those subsidies on the "clean" and "dirty" goods, and the elasticity of demand for those goods in other regions. When adopted by small jurisdictions, these price impacts are likely to be small. It is worth pointing out that command and control mandates, as discussed previously, can also have an indirect effect on prices for the dirty goods. Specifically, when a locally applied standard causes firms to adjust production, for example by relocating plants; the cost of production will go up because the standard has forced firms to make suboptimal decisions. If these higher costs are passed on to consumers, demand for the dirty product will fall. For small jurisdictions, these spillover pricing effects are likely to be small and even negligible. However, from a practical perspective, local regulators need to determine whether the price impacts of a policy produce less damaging spillovers than the leakage and reshuffling effects.

Perhaps the biggest drawbacks of targeted subsidies are the practical barriers to implementing them effectively. Even with skilled and dedicated regulators, the information required to pick the "right" technologies is daunting. So there is considerable risk that large subsidies will go to technologies that would not prove competitive under ideal regulations. Politicians and regulators are in effect placing large bets that the expected economies of scale and learning will in fact materialize. Even when these benefits do not appear, there are often calls for continued subsidies, preventing some "infant" industries from ever growing up.

There is no question that politics also play an important role in the subsidies game. For example, many argue that USA's focus on corn-based ethanol has been significantly influenced by the Midwestern farm-belt (see Gardner 2007; Wall Street Journal 2007). Federal tax incentives for the purchase of hybrid-fuel cars were deliberately designed to favor those producers who sell hybrids in smaller volumes, who

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[6] For ease, we use biofuels as an example of a transportation fuel that generates lower carbon emissions than petroleum products. However, questions have recently been raised about whether using ethanol in fact leads to lower carbon emissions (Searchinger et al. 2008).
[7] See Holland, Knittel, and Hughes (2007) for a detailed examination of this point.
[8] This phenomenon is sometimes referred to as demand-side leakage, which we discuss in more detail in the next section. It is worth noting that a reduction in natural gas prices has been cited as a benefit of aggressive adoption of renewables (see Wiser, Bolinger, and St. Clair 2005).

also happen to be US auto manufacturers. Of course, it could be argued that politics plays a role in just about any regulation or public policy. However, because subsidies often involve direct transfers of money to certain parties, they appear to be even more vulnerable to these pressures than other regulations. Moreover, once subsidy programs are set in place and are conferring direct benefits to specific groups, it becomes politically difficult to remove them.

Problems with Local Application of Environmental Regulations

Based on the discussion in the last section, from an efficiency perspective, market-based regulations are more appealing than less-flexible regulations or subsidies. However, when one is considering the local regulation of a global pollutant, such as GHGs, the situation becomes more complicated. This section discusses the problem of circumvention, specifically leakage and reshuffling, when environmental regulations and policies are applied locally.

Leakage

Perhaps the most obvious way for polluters to circumvent an environmental regulation is to relocate the regulated facility and its polluting activities to another jurisdiction. Following the literature, we refer to this physical relocation of facilities as leakage (see, for example, Fowlie 2007 and Kuik and Gerlagh 2003). There is also the phenomenon of demand-side leakage, whereby a local regulation that depresses demand for a polluting goods in one region can lead to higher quantities demanded of the goods in unregulated regions (see Felder and Rutherford 1993). We will focus here on supply-side leakage, although we comment on the relationship between demand-side leakage and reshuffling when we discuss reshuffling below.

When differentially applied across regions, mandates and standards can lead to leakage. For example, under the Clean Air Act (CAA), more stringent and costly emission standards apply to nonattainment areas. Research has demonstrated that industrial activity declines in nonattainment areas and is at least partially displaced by growth in attainment areas, where regulation is less costly (see Greenstone 2002 and Becker and Henderson 2000).To the extent that this displaced production emits at higher, less regulated rates, pollution has leaked from the heavily regulated region to the more lax region.

Market-based regulations are equally vulnerable to the problems of leakage. For example, if one jurisdiction imposes a tax on emissions or establishes a cap-and-trade system, it will be more expensive for firms to produce their pollution-intensive goods. This creates an incentive for firms to move some of their production elsewhere. They may accomplish this by producing slightly less from their regulated plants and more from their unregulated plants, or by moving their particularly pollution-intensive plants out of the regulated region.

When considering the leakage of polluting sources away from areas of stringent regulation, it is critical to recognize the varying impacts of local pollution. For example, many of the CAA criteria pollutants cause damage close to where they are emitted, with the classic example being ground-level ozone, which contributes to smog. Therefore the relocation of polluting sources is not necessarily a bad outcome (see Becker and Henderson 2000).

However, the relocation of polluting sources may not improve the local environment. This may be the case if the plants move "upwind" of the regulated region, or if the region applying the standard is very small relative to the geographic scope of the environmental problem. In this regard, climate change represents the most extreme and challenging case. This is because the location of GHG emissions does not influence their impact on the climate. When it comes to climate change, everywhere is upwind. The global public good aspect of the climate is therefore one of the great challenges to formulating climate change policy (see Nordhaus 2007). To the extent that local regulations cause outmigration or "leakage" of regulated facilities, rather than a true reduction from local sources, the local environment will not improve.

Until now, we have not distinguished between standards imposed on firms, such as emissions limits for plants, and standards imposed on individuals, such as energy efficiency standards for homes. While leakage is possible with both types of standards,[9] leakage is generally less likely to be a problem at the individual level largely because trying to avoid the standard can be more costly than meeting it. For instance, few people choose to live in Nevada instead of California simply to avoid the residential energy efficiency standards in California.

Despite all the potential disadvantages of targeted subsidies, they do have the advantage of being less vulnerable to leakage. Because they do not impose costs on firms, firms have no reason to relocate production to avoid them. To the contrary—subsidies are often touted as a way to attract new firms or even industries to benefit the local economy. Therefore, smaller jurisdictions, such as US cities or states, may find subsidies more appealing than other regulatory tools that can be more easily circumvented. In fact, subsidies may be the only means to meaningfully impact emissions on a local level.

Reshuffling

We now turn to a related problem that can arise when regulations are imposed at the point of purchase, but where some consumers are subject to the policies and others are not.[10] If a sufficient percentage of the products affected by a regulation already complies with it, the policy's goals can be achieved by simply reshuffling who is buying from whom. This will make the policy completely ineffective, as it will not alter the rate at which the favored product is produced. For example, assume that California accounts for 10 percent of the world sea bass market, and that it adopts a regulation stating that only sea bass caught using sustainable fishing techniques can be sold in the state. If more than 10 percent of sea bass in the world market is already caught using sustainable techniques, these fish can be diverted for sale in California. So, even if Californians had

[9] For example, homeowners may build just outside a local area to avoid zoning restrictions, or consumers may purchase on the Internet in order to avoid local sales taxes.

[10] Ironically, policy makers are often attracted to consumer-based regulations either because much of the production takes place outside of their jurisdiction or because they fear that regulating only producers within their jurisdiction will lead to leakage.

previously been consuming some non-sustainable fish, their ban will have no effect on the way fish are caught worldwide as long as consumers outside of California are indifferent between sustainable and non-sustainable fish.[11]

As the above example demonstrates, the reshuffling problem is similar to the conditions that limit the effectiveness of consumer boycotts. Although a percentage of motivated customers stops buying from the boycotted source, there will be no net impact on sales or prices if there are enough other price-sensitive customers who are indifferent to the cause of the boycott and willing to shift to the boycotted producers. As with an ineffective boycott, reshuffling is more likely when the share of products that already comply with a policy is larger than the share of consumers who are subject to it.

Note that both reshuffling and demand-side leakage affect demand outside the regulated area. Unlike demand-side leakage, however, reshuffling does not change total equilibrium consumption (or prices or emissions) of the regulated goods. Reshuffling requires that consumers inside the regulated region perceive the clean product to be a perfect substitute for the dirty product, and so substitute all their consumption to the clean product, while consumers outside the regulated region are indifferent between consuming clean or dirty goods, and so increase their consumption of the dirty goods. There is no such perfect substitute available with demand-side leakage. In fact, there is a duality between reshuffling and demand-side leakage, since if firms are able to reshuffle completely, there need be no change in prices and therefore no demand-side reaction to the regulation. It is only to the extent that firms are unable to avoid the regulation through reshuffling that there is a real reduction in emissions in the regulated jurisdiction through new, clean supply or reduced dirty consumption. In the latter case, there could be demand-side leakage if the reduced dirty consumption in the regulated region drives down the price for the product elsewhere.

California's deliberations regarding the establishment of fuel economy requirements on vehicles sold within its borders (through AB 1493) provides an example of the potential for reshuffling under a regulatory standard. The standards initially required higher fuel economy than is required at the federal level under the Corporate Average Fuel Economy standards. As initially structured, the standard may have encouraged car manufacturers to sell less fuel-efficient vehicles in other parts of the country than they would have sold otherwise and yet still meet national standards, which are based on national average fuel economy. This could result in a reshuffling of car sales and not necessarily a real reduction in emissions (see Stavins, Jaffe, and Schatzki 2007). Ultimately, an agreement was reached that aligned the state and national standards. Such an agreement reduced the reshuffling concern and increased the national standards, but also resulted in California implementing less ambitious reductions than proposed.

There are conditions under which a more aggressive policy such as a California fuel economy standard could have a meaningful impact on the national fleet. Specifically, if a jurisdiction is large enough, a local standard may force an industry beyond a tipping point, where it is less costly to produce all goods, even those sold outside the regulated region, to comply with the local standard. In this case, the local standard, far from being

[11] The result that reshuffling will have no effect on market equilibrium assumes that there are no transaction costs associated with rematching buyers and sellers.

bypassed, actually gets leveraged onto other regions. In a related fashion, previous California regulations to limit pollution from vehicles have often led, in due time, to the adoption of equally stringent regulations at the national level. Some observers credit the California regulations with demonstrating to car manufacturers and federal regulators that lower emissions can be achieved relatively cost effectively.

Similarly, indirect subsidies, which promote clean technologies by requiring consumers to purchase them, can be vulnerable to reshuffling. Consider the case of the LCFS as implemented by California. In assessing the carbon content of various transportation fuels, the California LCFS takes a life cycle approach by tracking the environmental impact of fuel production up the supply chain. For example, ethanol produced from lower-carbon crops and using lower-carbon farming methods would earn more credit under the California proposal than dirtier ethanol. Similarly, gasoline refined from light crude oil would receive a slightly higher credit (or lower penalty) than gasoline refined from heavy crude oil. If the California policy favors clean ethanol, then consumers in other states will buy the dirty ethanol previously purchased by Californians. If California's demand for clean ethanol under the LCFS is less than the existing supply of clean ethanol, this policy will have no impact on ethanol farming practices.

A consumption-based application of cap-and-trade can also fall victim to the reshuffling of production. In the next section we discuss in detail an example of this problem in the context of the California electricity sector. Reshuffling is not just a problem with a cap and-trade system—it can also occur under an emissions tax, as long as the tax is levied on consumers and not producers. For instance, if gasoline consumers in California were charged higher prices for gasoline refined from carbon-intensive sources such as heavy crude oil or oil sands, producers would have an incentive to divert products from lower carbon sources to California.

Barriers to Leakage and Reshuffling

Clearly, regulatory jurisdiction can cause serious problems when environmental regulations are applied locally to pollutants, such as GHGs, whose damages extend beyond the jurisdiction of the regulator. We have argued that subsidies, in particular targeted subsidies, are less vulnerable to leakage or reshuffling. However, it is important to note that transaction costs and other barriers can influence the extent to which buyers and sellers can circumvent local policies.

A key consideration concerning leakage is the cost of changing the physical source of production. Assuming that production was sourced efficiently prior to the imposition of environmental regulations, any change in that production would involve some increase in costs. These costs could range from an increase in transporting goods, to the physical relocation of entire production facilities. Constraints on import capacity, such as pipeline, transmission line, or port-facility capacities, can limit the feasibility of leakage. In many cases these costs may exceed the costs of the environmental regulation, making leakage unprofitable.

The transaction costs of reshuffling appear to be less severe as reshuffling does not involve the relocation of production; it simply rearranges where products are shipped. Assuming that transportation costs were minimized before the implementation of the policy, reshuffling would only increase the costs. This could be true of attempts to favor different sources of ethanol under a LCFS for example. Electricity provides a special case since electrons cannot be tracked to particular generators. As a result, reshuffling in the electricity sector is more of a financial arrangement than a physical activity.

Institutional factors, such as overlapping government regulations or limitations, may also reduce the extent of reshuffling and leakage problems. For example, electricity sales from federally owned water projects in the US favor certain customer classes, and it may prove difficult for these customers to resell their subsidized power. In the specific context of climate change policies, many of the large emitters of GHGs are either regulated or government owned. The strong influence of government on those firms' decision making can limit their incentive or ability to execute leakage or reshuffling strategies.

That said, as we describe below, the problems of leakage and reshuffling are of more than academic concern when it comes to local GHG policies. If states act unilaterally, without the participation of other states in their regions, these problems could seriously undermine the impact of the regulations.

Climate Change Policies for the Electricity Sector

In this section, we describe specific regulatory policies aimed at reducing carbon emissions from the electric power sector. We focus on the experience in California because it has adopted a wide range of policies, but we also discuss initiatives in other regions of the country. In each case, we assess the potential for leakage and reshuffling.

Emissions standards

California senate bill 1368 establishes a standard for emissions from plants providing "baseload" power to "load-serving entities" (LSEs), the firms responsible for either producing or purchasing electricity for end-users in California. The law requires that new energy purchases and investments by California LSEs be directed exclusively towards low-carbon power plants.[12] In Bushnell, Peterman, and Wolfram (2007) (hereafter BPW 2007), we demonstrate that there are already ample resources outside of California that comply with this emissions standard. California utilities can comply with the standard by buying from the existing low-carbon sources, and leaving new or old "dirty" sources to meet the demand from other states (see BPW 2007).

Efficiency standards can have a meaningful effect if they apply to choices that are inherently local—such as residential and commercial building and lighting standards—where leakage is not a serious issue. In fact, California has had a long tradition of enacting energy efficiency standards for homes and appliances. For this reason, and because California's standards have often been adopted at the national level, its energy

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[12] Specifically, the law requires that power plants that LSEs invest in, build, or buy power from under long term contract must meet a standard that limits their emissions to be no greater than those from a current combined-cycle natural gas plant.

efficiency program has likely had a meaningful impact on emissions from the electricity sector (see Geller 1997).

Subsidies

Regulators have adopted a wide variety of initiatives to encourage specific alternative energy technologies for producing electricity. For illustrative purposes, we will focus our discussion on two prominent programs that represent different implementation philosophies: state-level renewable portfolio standards and the California Solar Initiative (CSI).

As of 2016, 29 states and the District of Columbia have adopted renewable portfolio standards. While the details of their implementation vary, these policies share the common characteristic that they impose a requirement that electric utilities within the state meet a certain percentage of their demand with energy from renewable sources. Conceptually, a renewable portfolio standard (RPS) does not target a specific technology, but rather a class of technologies, for preferential treatment.[13]

In theory an RPS could be subject to reshuffling. For example, if California imposed an RPS, and significant amounts of renewable supply already existed in the western states, California utilities could comply with the RPS by purchasing from existing sources. In practice, the policies have been, and seem likely to continue to be, strongly binding regulations that are dramatically changing the procurement practices of electric utilities. This is because the renewable capacity necessary to meet many states' RPS obligations does not yet exist. With so many states enacting an RPS, the option to comply by exporting dirty power and importing the renewable energy from other states is limited.

While the RPS favors all renewables, several states and cities have adopted policies to promote specific alternative energy sources. Perhaps the most ambitious of these in the US is the CSI. The initiative is a set of direct subsidies to property owners who install solar photovoltaic systems on their buildings.[14] The CSI targets 3,000 MW and includes investor-owned and public utilities programs. The programs operate from 2007 through 2016 and will allocate up to $2.8 billion in subsidies, financed from general electric rates. The program represents a classic example of a targeted subsidy, and is generally immune from leakage and reshuffling. Californians have clearly been responding to these subsidies. The programs have been well subscribed with the investor owned-utilities' CSI program reaching in early 2015 its general market target of 1,750 MW. However, as often happens with targeted subsidies, some have questioned whether the California regulators were wise to invest so much money in this particular technology. At the beginning of the program, proponents of the CSI program claimed that an expansion of solar PVs in California would spur new efficiencies in their design, production, and installation and local economic investment in the industry (see Jurgens

[13] RPS policies in fourteen states do require some portion of the RPS to be met with a specific technology, but these amounts are small relative to the total RPS requirement.

[14] The original subsidy was adopted by the California Public Utilities Commission. In 2006, Senate Bill 1 extended the program to most municipal utilities.

2006; US Newswire 2006). Critics, on the other hand, pointed out that an injection of even several hundred million dollars per year into the worldwide solar PV market while significant, would hardly constitute the dramatic, transformational change in demand necessary to capture needed efficiencies (see Borenstein 2008). Moreover, when the program started, current-generation solar PV seemed a curious technology to bet on given its high cost. In the years since the program was launched, various technology, financing, and policy innovations have led to a significant worldwide reduction in rooftop solar costs resulting in solar PV becoming more cost-effective for a class of customers. How much of this cost decline is attributable to the CSI subsidy is debatable. However the incentive program is viewed as a key contributor to the growth of, and public acceptance, of California's solar PV market.

Market-based regulations

Currently, two areas of the country use cap-and-trade programs to regulate GHG emissions from the electricity sector: a consortium of 9 northeastern and Mid-Atlantic States, organized as the Regional Greenhouse Gas Initiative (RGGI), and California. RGGI is the first US mandatory cap-and-trade program to control carbon dioxide emissions. Begun in 2009, the original cap did not results in additional emissions reductions due to various factors including an economic downturn, an economic shift to less carbon intensive fuels, and some elements of the cap design. In response, RGGI reduced its cap in 2014 to be 91 million tons – a reduction of 45 percent from the previous cap. The cap then declines 2.5 percent each year from 2015 to 2020. California's first GHG legislation, AB 32, articulates an overall goal of reducing California's GHG emissions to 1990 levels by 2020. California legislation SB 350, enacted in 2015, extends the target to a 40% reduction in greenhouse gas levels relative to 1990 by 2030. Unlike RGGI, the scope of the California legislation extends well beyond the electricity industry to include most major sources of GHG emissions.

There are two possible approaches to measuring the amount of emissions from the electricity industry: a consumption-based metric and a production-based metric. RGGI has adopted a production-based approach and California adopted a hybrid production and consumption-based approach. This hybrid approach regulates imported electricity through a consumption-based system and local sources through a production-based system (CPUC2008b). It is instructive to consider the possibilities for leakage and reshuffling under both a production and consumption based approach.

Since some of the RGGI states participate in markets with generators outside of the cap and-trade program, concern has been raised about emissions leakage under a production based system (Northeast Regional Greenhouse Gas Coalition 2005; RGGI Emissions Leakage Multi-State Staff Working Group 2007b). Debate persists regarding the extent to which such emissions leakage has and will occur, particularly since the magnitude will be affected by location specific factors and allowance prices. A pure production-based standard has never really gained traction in California, presumably because a substantial fraction of California's electricity and a majority of the GHG emissions come from plants outside of California.[15] Therefore, reducing emissions to 1990 levels only from plants within California would not accomplish as much in terms of emissions levels as a similar reduction in emissions from all plants that sell to California. Also, there is a significant risk that a production-based standard could be circumvented by simply increasing net imports from outside of California (i.e., leakage). Absent additional limitations, these imports would count as perfectly "clean" under a production-based standard.

However, the regulation of imports through a consumption-based approach could be significantly undermined by reshuffling, as we have demonstrated in other work (see BPW 2007). The analysis referenced below reflects data and forecasts available in 2008 when the analysis was conducted and published. Specifically, to examine whether there is enough low-carbon capacity to meet California's GHG goals for electricity, we use a projection of California's 2020 electricity demand of about 340 terawatt-hours (TWh) (see BPW 2007 or Appendix included here for the assumptions underlying this projection). [16] Since the CO2 emissions from meeting California's electricity demand in 1990 were approximately 80 million metric tons (MMT), we use this as the target for 2020.

We analyze power plant operations in the west in 2004 to determine whether it is possible to meet California's GHG goals with existing western electricity production, which would limit the regulation's impact on investment. In 2004, there were 265 TWh of output from zero carbon sources, mainly large-scale hydro and nuclear plants. The emissions of CO2 necessary to meet the remaining 75 TWh of electricity demand in 2020 (75 = 340 − 265) would be only 30 MMT of CO2, well below the 1990 level of 80 MMT. This suggests that California could procure power in the western markets from existing sources without exceeding 1990 carbon emissions levels. It also implies that a consumption-based standard for California is at serious risk of circumvention if utilities in the western states reshuffle their energy sources. Since this analysis was conducted changes in a few factors may influence whether sufficient renewable supply exists in the west to meet California renewable demand. California's load forecasts for 2020 have declined from 2005 predictions and renewable self-generation has increased. Both of these trends make it easier to reach California's target. However, California's RPS target has increased from 33% in 2020 to 50% in 2030, which results in a higher need for renewables (although the 2020 target remains the same.) Moreover, these calculations reflect many important underlying assumptions about the ability and willingness of western electricity firms to trade their electricity. It is intended as an illustrative example of the potential severity of the problem, rather than a forecast of what is likely to happen.

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[15] The accounting of production is complicated somewhat by the fact that there is coal capacity owned by (or contracted to) California LSEs that is located outside of California but connected in such a way that, electrically, it is treated as within California. In 2004, over 29 TWh of electricity generation was attributed to plants that fall in this category (McCann et al. 2006).

[16] As noted in BPW (2007) and the appendix this analysis assumed an average 1.98% growth in electricity demand from EIA reported 2005 demand for all western states. California demand has grown at a lower rate than predicted. The 2016 California Energy Commission 2016-2026 demand forecasts assume a 0.97% growth rate and a mid-case forecast of 296.244 TWh 2020 electricity demand in California.

That said, BPW (2007) considers several of the most likely impediments to a complete reshuffling of energy sources,[17] and concludes that California is not a large enough player in the western electricity market to cause substantive changes with a cap-and-trade policy unless it undertakes additional regulatory intervention. Because of such concerns, California regulators have considered various administrative rules relating to the accounting of emissions from "outside" the regulated region that could reduce, or even eliminate, the incentives to reshuffle purchases. Most solutions would involve setting a default emissions value that would be used to measure emissions from imported power no matter what the source, and then limiting the ability of California utilities to claim as imports emissions from facilities whose emissions are cleaner than this default.[18] For instance, California regulators have proposed excluding existing hydro and nuclear plants from the set of sources eligible to be claimed as imported power. These rules dilute the incentives for existing firms located outside the region to actually reduce emissions. They also blunt the accuracy of emissions measurement and could draw legal challenges.

The reshuffling in the electricity sector could reduce the effectiveness of AB 32 in other sectors. If the cap-and-trade system allows trading across sectors, then electric companies could sell any excess allowances they create by reshuffling. Firms in other sectors could purchase these allowances instead of actually reducing the carbon emissions from their production processes.

A far better outcome for the fate of a cap-and-trade program would be the expansion of its jurisdiction. Over the years attempts at expanding the cap-and-trade program to other states have occurred, including ultimately unsuccessful efforts in 2007 by California Governor Schwarzenegger to create a regional cap and trade system between California, Arizona, New Mexico, Oregon, and Washington. With this in mind, BPW (2007) examined a policy that would include the five states that were parties to the agreement.

We find that a five-state production-based policy would likely help to induce (or reinforce) a decision to retire a few coal plants by 2020. However, the key question is: what kind of capacity would replace those plants and generate the additional energy required to meet load growth in this region? The problem again with a production-based standard is that this additional demand could be met from new facilities located outside of the five-state block. If the new plants are coal-fired, this would clearly not help to reduce GHG emissions.

Under a consumption-based standard, the imports would, in theory, be judged based upon the carbon content of their sources. There are significant amounts of zero-carbon hydroelectric capacity outside of the five states (including in Canada). In addition, if sufficient capacity is built to comply with the various RPS policies enacted by the five

[17] The BPW (2007) analysis excludes purchases from the Bonneville Power Administration, the largest source of federally owned hydropower, and assumes that emissions from all sources within California will be counted. This could reflect regulatory constraints on reselling this power out of California to avoid AB 32 or it could reflect transmission constraints that limit imports to their 2004 levels.

[18] For example, power purchases could be tied to a historic reference year, rather than actual current purchases. Thus a firm that bought power from a coal plant in 2000, for example, would be responsible for the future emissions from that same plant, whether or not it continues to buy power from it.

states, the zero carbon energy from these sources will account for about half of our load-growth projections. This suggests that 1990 emissions levels could be met if a small amount of new zero-carbon generation were added anywhere in the west (BPW 2007).

In sum, our analysis suggests that even if carbon limits are expanded to cover Arizona, New Mexico, Oregon, and Washington, the policy tool that is likely to have the greatest impact on reducing the carbon intensity of electricity generation is the renewable portfolio standard. This highlights an important consideration in regulatory policy design—that several different regulatory instruments are often applied simultaneously. We address this topic in the next section.

The Interaction of Regulatory Options

Often, debates over the choice of the appropriate regulatory instrument fail to take into account the fact that any regulation is likely to coexist with a host of other regulations that can affect the problem of interest. This issue is particularly relevant when discussing market-based environmental regulations. The key advantage of market-based mechanisms is that they afford the regulated industry more flexibility as to how, and even how much, to comply. However, this flexibility can be greatly reduced when the market-based mechanism is overlaid onto a series of other regulations. Nowhere is this truer than in the electricity industry, with its history of strong economic and environmental regulation.

Overlapping regulation can have both negative and positive impacts. Research has shown that the economic regulation of firms, rather than a motivation to minimize costs, can determine a firm's choice of compliance option under a cap-and-trade system (see Fowlie 2006). This can, for example, lead to investments being made in capital-intensive pollution control by firms with the most favorable regulatory treatment, rather than those with the lowest cost.

On the other hand, when the market-based regulation is applied only locally, traditional regulatory instruments can limit the leakage and reshuffling problems that would otherwise arise. Indeed, regulators in both California and the RGGI states have expressed a commitment to use energy efficiency standards and to promote alternative energy while developing a cap-and-trade system. Both regions are relying on these other measures, in part, to limit the problems of a localized cap-and-trade market (RGGI Emissions Leakage Multi-State Staff Working Group 2007b). Yet these measures, which include aggressive commitments to renewable energy and energy efficiency, as well as direct oversight of the procurement decisions of regulated utilities in their regions, will no doubt limit the impact of the cap-and trade program. California's electricity industry may be the most extreme case, with many different regulations directed at reducing GHGs. In addition to funding for energy efficiency and an RPS target of 50% percent of energy consumed by 2030, there are also explicit penalties and laws aimed at preventing investment in new coal-fired plants. California's RPS and energy efficiency programs alone will meet all of the state's load growth, leaving compliance with AB 32 down to reducing current emissions to 40% below 1990 levels. With California's initial AB32 greenhouse target of 1990 levels by 2020, BPW (2007) analysis showed that increasing the RPS to 33 percent and increasing energy efficiency, demand response, and PV alone

alone would enable California's electricity sector to reach its 1990 emissions levels and be in compliance with AB32, without engaging in cap and trade.[19] However, the substantial increase in the greenhouse gas target for 2030, and the potential role for transportation electrification, now enable a greater role for the cap-and-trade program for electric sector compliance.

Summary and Conclusions

Local regulators are at a disadvantage when they attempt to regulate emissions of pollutants such as GHGs, which are damaging even when emitted outside the regulator's jurisdiction. There is a significant risk that because of their limited scope, certain types of local policies could be undermined either through the exodus of physical plants, along with their emissions, to unregulated regions, or through a reshuffling of deliveries to customers within and outside the regulated area.

We have argued that leakage problems are most pronounced for regulations that impose costs on firms, as the firms are more likely to find it profitable to move to jurisdictions where they will not incur the costs. Firms may also move into a jurisdiction that is subsidizing clean technologies. Reshuffling problems can arise with both cost-imposing and subsidizing policies, but they are more pronounced with more flexible policies, such as a cap-and-trade system. This implies that regulatory mechanisms such as mandates or subsidies for specific clean energy sources or energy efficiency standards, although less efficient when applied on a large scale, may be the only kinds of regulations that can produce meaningful results at the local level.

In our survey of policies to reduce GHGs from the electricity sector, we have noted that local regulators are keenly aware of the potential for leakage. In several instances, concerns about leakage have caused regulators to consider regulating consumers rather than producers. Unfortunately, regulating consumers works much like a government-imposed boycott, and is only effective if the boycotting consumers make up a sufficiently large share of the relevant market. Thus, although there may be reasons for local regulators to target consumers instead of producers, avoiding leakage is not one of them.

Our analysis raises an important question. What are local regulators actually trying to achieve with their GHG emissions policies? Are the goals truly limited to forcing down the carbon footprint from activities within their jurisdiction? If so, one must keep in mind that the net GHG reductions from the policies proposed by a locality as large as California, assuming it achieves all its goals, would amount to orders of magnitude less in reductions in greenhouse gases than countries' such as China are predicted to add to the atmosphere. This fact makes it clear that local initiatives are largely symbolic unless they can also facilitate change beyond their local regions. Thus it is useful to consider those policies that are the most likely to have broader impacts, either by making it easier for other jurisdictions to adopt effective GHG regulations or by

[19] The California Energy Commission's Scenario 5A, "High Energy Efficiency and Renewables in CA only," which includes such aggressive scenarios, predicts 2020 carbon emissions to be close to 1990 carbon levels (CEC 2007b, p. 130).

influencing these technologies that are available to reduce emissions. Here it is important to consider how generally applicable either the regulatory or technological lessons are.

For all of the reasons discussed in this paper, the experiences with local regulations appear unlikely to have much bearing on their effectiveness at a broader level. For example, while California cap-and-trade policies for the electricity industry may be easily undermined by reshuffling and leakage, these issues are much less likely to be a problem on a national level (electricity is not a globally traded commodity). But given political realities, an ineffectual California policy may make it less likely that a federal cap-and trade policy will be adopted, even if the problems California experiences are unlikely to be replicated for a broader scale policy. Nevertheless, if local policies lead to what are effectively demonstration projects of various technologies, their successes or failures could be important first steps in adopting effective low-carbon technologies on a more global scale.

Paper 1 Appendix

This appendix describes the data sources and underlying assumptions reflected in the analyses described in the text.

Supply

Overview:

2004 WECC (and sub-NERC region) energy supply (in MWhs) is from the Platts Powerdat database (www.platts.com) and is supplemented with Platts Basecase database. Platts' Powerdat supply data is from the RDI modeled production costs query and information is from EIA-906 and FERC form 423. From this database the following plant level data is used: MW, net generation (MWh), capacity factor, prime mover, primary fuel, plant owner, and heat rate. This database contains a separate record for each plant by prime mover type and by ownership. Since the policies under review address the unit instead of the plant, concern was taken to make sure that the data in this form does not overlook the important unit specific factors such as fuel use and capacity factors. This query produces 1,208 plants.

Platts Basecase database (Utility/Non Utility Unit Ownership query) was used to supplement the Powerdat data with plants less than 50MW that were not captured in the main query. This database uses data from EIA forms EIA-411 and EIA-860. An additional 427 plants were added to the database with this method. Capacity factors for these plants are estimated using the average capacity factors for plants with the same fuel type already present in our database. For fuel types for which there was no know capacity factor, the average capacity factor (.474) of the database is used.

The total WECC energy supply used here does not include Canadian or Mexican plants in WECC. The WECC includes Washington, Oregon, California, Idaho, Nevada, Wyoming, Utah, Arizona, Colorado, the bulk of Montana and New Mexico, plus western portions of Texas, and South Dakota. It also includes the Canadian provinces British Columbia and Alberta, and the northern portion of Baja California, Mexico.

Mohave generating plant is included in the database; however the units currently owned by California utilities are not considered part of their portfolio due to reports that these utilities will discontinue their involvement with the plant. It was announced in 2009 that the plant would be permanently decommissioned.

EPS specific:

For the EPS analysis, supply with a capacity factor > 60% and hydro and wind facilities were designated as baseload. EPS-compliant plants are those plants that meet the baseload criteria and have a CO_2 emissions rate equal or less than 1,000lbsCO_2/MWh.

Demand

EPS specific:

Hourly 2004 demand data for the WECC and each of the WECC sub-regions is used to determine 60% demand. This data is from Platts Powerdat database (www.platts.com) and from its NERC Sub-Region Hourly Load query. This hourly load data is from EIA-704.

For all the NERC sub-regions baseload demand growth through 2012 is based on the 4 year average (2001-2004) of baseload growth in these sub-regions calculated using data from the Platt's NERC Sub-Region Hourly Load query (EIA-704). The resulting growth rates are: CAMX, 1.85%, NWPAUS, 1.23% AZ/NM/SNV, 2.61%, RMPA, 6.19% and WECC average of 2.14%.

AB32 specific:

2020 demand for the following states (AZ, CA, MT, NM, NV, OR, WA) is calculated using 2005 demand from EIA form 861 (Retail Sales of Electricity by State by Sector by Provider) and assumes an average 1.98% growth rate for each of the states. 1.98% is the 10 year average demand for states in WECC region (the above states plus WY, Utah, and ID). Various sources were analyzed to determine state level demand forecasts. However, uncertainty and discrepancies between sources as well as year-to-year volatility in demand levels has resulted in the use of the region's average of 1.98%. Other sources considered: 1. EIA 861 state level data average 5 year and 10 year historical growth rates (resulted in average state rates of -1% to 5%) The average for all states was 1-2%. 2. The WECC 2005 Information Summary provides a CAGR of 2.4% for the WECC region (which includes some states not considered in this analysis). 3. The California Energy Commission projects 2020 demand for CA using a 1.14% rate.

CO_2 emissions

1990 emissions data:

1990 emissions data is from the EIA's Electric Power Annual with data for 2005 (U.S. Electric Power Industry Estimated Emissions by State (EIA-767 and EIA-906)) and is used to determine the cap targets.

2004 emissions data:

2004 emissions data is used to determine the emissions from existing generation. It is assumed that in 2020 capacity factors and emissions rates will be the same.

Since emissions' data was not available for all plants, heat rate is used to estimate the CO2lbs/MWh emissions rate for all the plants. A regression of heat rate on CO2lbs/MWh was conducted using reported heat rate and CO2lbs/MWh data from a subset of plants for which such data was available from the EPA Continuous Emissions Monitoring Systems (CEMS) database. Plants were analyzed by fuel type and the following regressions were calculated:

	Mean CO2lbs/MWh	Mean Heat Rate/kWh
Gas Plants	1,519.6	12,638.4
Coal Plants	2,328.3	11,363.3

Fuel type	Year	CO2lbs/net MWH =	constant	SE of constant	B1HR(BTU/MWH)	SE of B1	t-test	P-value	R^2	Correlation
Gas	2000-2005		14.9536	18.7	0.0001191	6.54E-07	181.92	0.000	0.976	0.9881
Coal (SUB and BIT)	2000-2005		2.95696	7.5	0.0002046	6.58E-07	310.97	0.000	0.997	0.9987

The CO2 emissions rate for the following fuels, geothermal, wood, biogas, refuse, and landfill gas, were estimated due to lack of sufficient data to run a regression analysis. The records that were available for these fuel types all had CO2 emissions rates of zero, leading to the assignment of zero as the appropriate CO2 emissions rate for these fuels. Due to limited data, oil and petroleum coke emissions were estimated using the coal regression. Oil emissions are similar to coal (1.969 lbs/kWh as compared to 2.095lbs/kWh) and both fuel types have similar heat rates. These fuel sources represent 4.4% of the total MWs.

Heat rates

Heat rates for plants are from the previously mentioned Platts Powerdat and Basecase databases. Average heat rate calculation: Calculated by dividing the total Btu content of fuel burned for generation by the resulting net kilowatt-hour generation. Calculation is as follows: sum of [(fuel quantity X conversion factor: 42(oil)/1,000(gas)/2,000(coal/trash/wood))*fuel BTU]/net generation MWh. For example, a station that burns 45,570 tons of coal rated at 11,461 btu/lb, producing 110,700 MWH would have a heat rate calculation = ((45.570*2000)*11461) divided by 110700, = 9436 heat rate.

RPS

Information on the RPS programs of states in the WECC is from The Database for Incentives for Renewables and Energy Efficiency. http://www.dsireusa.org/. Expected RPS TWhs is calculated as: % target*2020 demand forecast. See above for more detail on state demand forecasts.

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Pass-Through of Solar PV Incentives to Consumers: The Early Years of California's Solar PV Incentives

Introduction

Public subsidization of desirable goods, such as low-carbon energy, aims to reduce the private price of, and increase demand for, these goods. In practice however, the extent to which such incentives pass through to reduce final consumer prices varies due to market conditions. Incidence is the analysis of the pass-through of a particular subsidy or tax to a consumer and is the difference between an individual's available resources before and after the subsidy has been provided. Incidence analysis is about price, not quantity, changes.

Solar PV incentives pass-through to consumers is of particular importance to California since it has statutorily provided significant cash incentives to consumers for solar PV over the last two decades. Solar PV is promoted by the state to meet targets to reduce greenhouse gas emissions and local air pollution, increase energy independence from imported natural gas, diversify the state's energy mix, and generate domestic energy jobs.

The final price consumers pay for solar power is a key metric of the success of these incentive programs and overall PV market performance. Policymakers and advocates have opined on how subsidies should lead to consumer price declines. Regarding the effectiveness of previous California solar incentive programs, the 2006 policy director of Environment California, the sponsor of the California solar bill Senate Bill 1 noted, "By lowering prices and growing demand, both of these direct consumer rebate programs (ERP, SGIP) have been major drivers of California's modern solar power program." (Del Chiaro and Gibson, 2006). The expectation that incentives should drive down solar PV purchase prices, and not just spur demand, was clear in the first version of Senate Bill 1 introduced by California Senator Kevin Murray. The bill identified that the proposed solar incentive program incentives "shall benefit the end-use consumer of the renewable generation by directly and exclusively reducing the purchase price or lease cost of the eligible system…" (Murray, 2004).

This incidence study, which I formally define in Section II, examines the early years of California's most recent wave of distributed solar PV incentives (2000-2008) to determine the pass-through of incentives. Examination of this period is worthwhile due to the high level of incentives provided and subsequent high cost to ratepayers; policymakers' expectations that price declines accrue to consumers; and market structure characteristics that might contribute to incomplete pass-through. Whether expectations of incentives' pass-through align with reality is critically important in the beginning years of emerging clean energy technology programs since this can affect the likelihood of future government investments and public support. Given the often-held policy assumption that consumer prices are declining in response to incentives, it is useful for policymakers to understand the circumstances under which such an assumption may not hold.

My results indicate that the pass-through of solar PV incentives during the 2000s to consumers was incomplete and did not reduce consumer prices as much as some supporters may have expected.

This period of California's subsidies included net metering, various upfront cash incentives, and tax credits. These government incentives were viewed as critical for making distributed solar PV accessible to homeowners. In 1995, California passed its first net metering law, Senate Bill 656, which compensated solar PV producers for excess solar generation at the retail electricity rate. In 1996, Assembly Bill 1890 created the Emerging Renewables Program, which provided cash incentives for residential and commercial solar PV system less than 30 kW. In 2000, Assembly Bill 970 created the Self-Generation Incentive Program ("SGIP"), which incentivized distributed solar PV systems 30 kW to 1 MW. After two failed legislative efforts, the California Public Utilities Commission administratively created the California Solar Initiative (CSI) – a 3,000 MW goal distributed solar PV mandate for investor owned utilities. In 2006, California Senate Bill 1 codified the CSI and expanded its incentives to public utility customers.

California has allocated billions of dollars to its solar PV incentive programs. This period was characterized by high incentives for solar PV although they did decline over time. The highest upfront cash incentives offered by the California programs were \$4.50/W, which represented approximately 40% of installed costs. By 2014 upfront cash incentives were phased out of California's market (except for low-income installations) and residential PV total installed cost per watt neared \$4.00. These incentives assisted with the financing of solar PV since during this period there was very limited third party (lease) financing available. Third party financing enables homeowners to purchase solar PV without a down payment, ownership, or payments higher than their monthly electricity bills. These leases have been credited with assisting homeowners in more recent years in overcoming the barrier that high upfront capital costs present for solar PV adoption. For systems 10kW or smaller, third party leases increased from 12% in 2007 to 65% in 2014 (Barbose and Dargouth, 2015).

As was noted earlier, California legislators were interested in the price declines and growth in demand for solar PV that incentives could spur. In addition, they were also concerned about the income differences in the pass-through of incentives. Specific concerns have been raised that incentives benefit only the wealthiest consumers who can already afford to purchase solar PV. Analysis of SB1 by California Senate Energy, Utilities, and Communications Committee consultant Randy Chinn notes, "For those who can afford it and who have a long term perspective, the PV program envisioned by this bill, in conjunction with the tax credits, makes installing a PV system an attractive option. But the cost of the PV system makes it impossible for low and middle income customers to even consider. As these customers will never be able to participate in the rebate program, the author and committee may wish to consider whether they benefit before making them pay for it." (Chinn, 2005).

Incomplete consumer information and supplier market power may also affect incidence and so it is useful to consider how these factors may have been present from 2000-2008. Game-theoretic bargaining literature suggests that a negotiating party who has incomplete information about the other party will obtain a smaller share of the surplus in the negotiation than if that party was better informed. Busse, Silva-Risso, and Zettelmeyer (2006) offer this a possible reason for their observation of different incidence rates for dealer versus consumer subsidies in the car market.

In the early years of solar PV incentives, consumers had less complete information regarding attainable solar PV prices and incentives. First, significant heterogeneity in solar PV prices existed in the late 1990s and early 2000s. As Barbose and Dargouth (2015) show, the range between the 20th and 80th percentile solar PV prices relative to median prices was especially pronounced during the early years, 1998-2004, of the US residential solar PV market. Price variability has narrowed significantly in the subsequent years. Regardless of the source of this variability, due to the lack of online comparison tools, early PV consumers had less means to compare system prices or available incentives. As the solar PV industry, the internet, and government incentive programs grew, searchable online resources such as findsolar.com, the California Solar Initiative database (Go Solar California), and New York's Solar PV Incentive Program Completed Projects by City and Contractor dataset emerged that facilitated attaining pricing information.

Moreover, information that was publicly available regarding incentives was not always reliable or clearly understandable. The Emerging Renewables Program, LADWP solar program, and New Solar Home Partnership, all adjusted subsidies at different times than initially proposed in their program schedules. Consumer eligibility for certain incentives was confusing given the overlap between programs, with publicly owned utility customers at times being eligible for investor owned utility programs. As programs matured eligible system sizes and price caps were introduced and changed. Moreover, how programs calculated total watts to be incentivized changed during the time period, and not necessarily at the same time the incentives changed. After 2008 all of the programs had more predictable incentive glide paths. Given the frequency of change and variation, I would expect customers to be less informed, and less able to predict, subsidy increases and declines. I think this reduced transparency may result in lower incentive pass-through during this period.

In addition, early solar adopters may have been less concerned about searching for the lowest prices or best incentives. Instead, as Garling and Thorgersen (2001) observe, early technology adopters are more focused on how technology prices compare to their internal reference price for what an innovation is personally worth to them as compared to what the actual cost is.

This period was also marked by a plethora of geographically limited installer firms, with some local markets served only by a few installers. Such conditions may lead to the exercise of market power and potentially less pass through. GTM Research and SEIA noted that it was in 2014 that the industry saw numerous in-state and national installers expand their sales footprints from one to two utility service territories and undertake unprecedented geographic diversification (GTM Research and SEIA, 2014). As Gillingham et al. (2014) observe, greater installer density is associated with greater competition, lower information search costs, and lower PV prices. Gillingham et al., focus their research on the 2010-2012 period, where they also find that some high demand areas do not have the lowest prices, suggesting some form of imperfect competition. All of these factors may lead to lower incentive pass-through to solar PV consumers in the early years of the market.

Models of Incidence and Relevant Literature

Subsidy incidence "falls" on the group (sellers vs. buyers) that receives the benefit of the subsidy. A subsidy can be passed forward to the consumer or backwards to the supplier. Pass-through to either of these groups can be full, e.g. 100 percent of the subsidy, incomplete, e.g. less than 100 percent (Graph 1), or in some circumstances over 100 percent. (Doyle and Samphantharak, 2008, Hamilton 1999, Katz and Rosen 1985, Stern 1987).

There are three rules of incidence. First, the statutory burden of the subsidy is not necessarily the same as the economic burden. Whether consumers or suppliers legally receive the subsidy is irrelevant to the distribution of the subsidy benefits. When a subsidy is offered to consumers in a perfectly competitive market or a monopoly market, the consumer will be willing to pay more for the subsidized good, so prices will rise, partially offsetting the statutory subsidy benefit to consumers. (Gruber, 2007, Ruffle, 2004). Second, the side of the market where the subsidy is imposed is irrelevant to the distribution of subsidy benefits. Third, incidence depends on the relative elasticities, i.e, price responsiveness, of supply and demand. Parties with more inelastic supply or demand benefit from the subsidies (or bear the greatest tax burden). For example, in a situation with perfectly inelastic supply, perhaps due to a labor shortage that limits all new entrants (Graph 2.2) the quantity of PV supplied remains the same regardless of the subsidy. In this situation, the supplier receives the full subsidy. In a situation with perfectly elastic supply (Graph 2.3), which would be expected in the long run for a competitive solar PV market, the quantity of PV demanded is available at a constant price and the full subsidy shifts to the PV consumer.

In public policy and academic arenas the issue of incidence in the energy sector has been more widely discussed as it relates to tax policy. For example, the consumer incidence of gasoline taxes was a political and equity concern for both President Jimmy Carter and President Clinton, and motivated their calls for income compensation for the poor affected by the pass-through of higher gasoline taxes to retail prices. Gasoline tax incidence also arose during the 2008 presidential campaign when Senator Hillary Clinton and Senator John McCain supported a suspension of federal gasoline taxes and then-Senator Barack Obama was in opposition. In the discussions, Senator Obama directly addressed the issue of less than complete pass-through of taxes when he noted "At best, this is a plan that would save you pennies a day for the summer months; that is, unless gas prices are raised to fill in the gap, which is just what happened in Illinois, when we tried this a few years ago," (Balz and Slevin, 2008). Although less commonly analyzed, subsidies are in essence negative taxes, and as such their pass through are subject to similar economic and distributional equity concerns.

There has been significant work on the incidence of taxes. Applied tax incidence studies typically assume full pass-through of taxes to consumer prices (Wiese, Rose and Schluter 1995, Zupnick 1975) although empirical evidence varies. Alm, Sennoga, and Skidmore (2009) and Marion and Muehlegger (1999) estimate full shifting of gasoline taxes to final consumers in the United States. Doyle and Samphantharak (2008) review the effects of sales taxes on retail gasoline prices in Illinois and Indiana utilizing incidents of tax suspensions and re-instatements and find that 70% of tax suspensions are passed to consumers in the form of lower prices, while 80-100% of the tax re-instatements are passes on to consumers. Besley and Rosen (1998) find evidence of full pass-through and some overshifting of taxes on U.S. commodity prices. In an analysis of the pass-through of state and local retail taxes on clothing prices during the post War World II period, Poterba (1996) finds full pass-through with retail rates increasing the same amount as the tax.

Subsidy incidence studies find a wider range of pass-through rates than tax studies. Studies of the pass-through rate of hybrid vehicle subsidies find incomplete to full incidence. Sallee (2008) finds almost complete shifting of incentives to hybrid vehicle consumers. However, Chupp, Myles, and Stephenson, (2010) find that sellers capture almost half of the federal tax credits for California hybrid cars. In the general car market, Busse, Silva-Risso, and Zettelmeyer (2006) estimate a 70-90% pass-through of cash rebate promotions for consumers, and only a 30-40% pass-through for dealer discount promotions.

Several recent examinations of the pass-through of solar PV incentives in California have yielded mixed results. Dong, Wiser, and Rai (2014) identify the pass-through of incentives in the California Emerging Renewables Program and the California Solar Initiative programs to residential customers using structural and reduced form modeling approaches. Using data from 2001-2012, they estimate a nearly 100% pass-through of incentives. Their reduced form model produces pass-through estimates of 83-103%, with greater variation in pass through rates across counties (32-270%). An earlier study, Wiser et al. (2006) offers evidence of incomplete pass-through of solar PV incentives in California. The authors find a pass-through of 50-80% across different specifications for two California subsidy programs.

Henwood (2014) finds a pass-through rate of 36% for the California Solar Initiative incentives for 2007-2013. He also finds that pass-through varies by zip code and that zip codes in the lowest quartile of median household income have a subsidy pass through slightly higher than the upper quartile. Podolefsky (2013) identifies the pass-through rate for the federal investment tax credit for solar PV to customers to be 17%. Gillingham et al. (2014) examine the source of heterogeneity in solar PV prices and find that higher consumer value of solar, defined as the combined discounted value of incentives and electricity savings, is associated with higher prices. The authors note that this result suggests that installers may be retaining some portion of this consumer value, i.e. incomplete pass-through.

Demand and supply constraints can affect how much of the subsidy passes through to consumers. Marion (2009) identifies a higher pass-through rate for diesel taxes when diesel supply is more elastic, such as times when untaxed diesel uses are of greater importance. Moreover, Marion finds that the pass-through rate is lower when US refinery utilization rate is high and capacity constrained. Similarly, Alm, Sennoga, and Skidmore (2009) offer evidence of less than full pass-through in less competitive rural markets (less elastic demand) as compared to urban gasoline markets. Chouinard and Perloff (2004) conclude that state specific gasoline taxes have a higher pass-through to consumers than federal taxes due to higher supply elasticity in certain states that is not present in the nation as a whole. Sallee (2010) presents evidence contrary to this trend in the Toyota

Prius market. Even in the presence of production constraints, Sallee finds that Prius prices did not shift and consumers still received 100% of the subsidy. Sallee posits that search frictions in the car market leads to this unconventional finding.

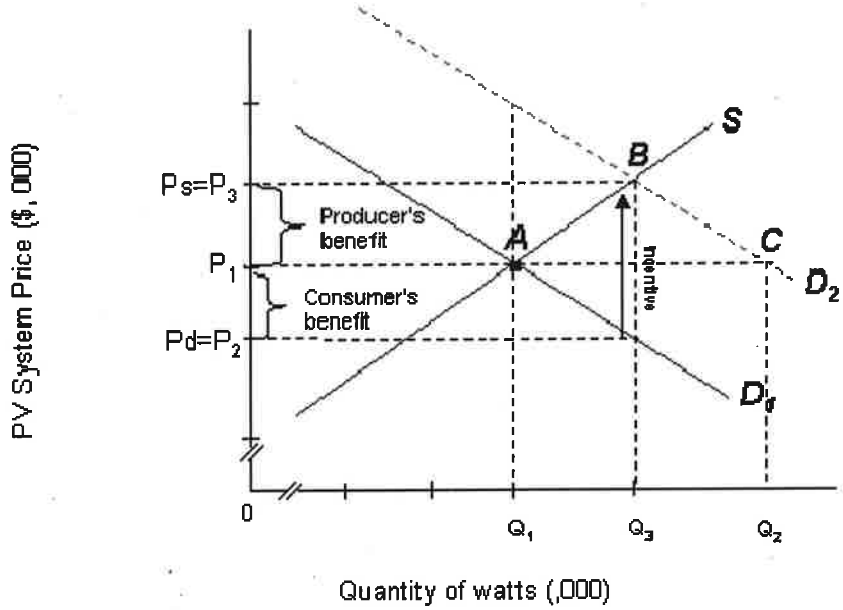
This paper contributes to the incidence and energy policy literature by evaluating the incidence of solar PV incentives in the early years of the most recent distributed solar PV demand pull programs. Review of this period is worthwhile due the high level of incentives provided and subsequent high cost to ratepayers; policymakers' expectations that price declines accrue to consumers; and market characteristics that might result in lower pass-through.

To determine incidence this paper employs a partial equilibrium model. Due to PV's relatively small share of the overall economy, the partial equilibrium model is preferable to a general equilibrium model. This model ignores where tax and subsidy proceeds are spent or originate and assumes a competitive marketplace. This is a reasonable assumption given that in the long-run the local solar PV market is not expected to be a monopoly market as there are no persistent barriers to entry. If it is a monopoly market, the pass through depends on the monopolist's marginal revenue and cost curves as well as the demand curve as detailed in graph 2.4.

It is most likely that currently the solar PV market is imperfectly competitive since higher search costs and some market power are likely present. Weyl and Fabinger (2013) extend the principles of tax incidence under perfect competition to imperfect competition models including monopoly, symmetric imperfect competition, and generally imperfectly competitive models. They find that the principles of incidence in competitive markets generally hold as well for imperfectly competitive markets. They also find that less competitive markets result in smaller pass-through rates.

Graphs 2.1, 2.2, and 2.3 offer hypothetical illustrations of the pass through of a consumer incentive on the final equilibrium price of a PV system under elastic and inelastic conditions. In the market there are two prices, the gross price and the after-incentive price. The gross price is the price received by the PV seller. This price is the same as the price in the market. The second price, the after-incentive price, is the price paid by the consumer who is receiving the incentive. The after-incentive price is lower by the amount of the incentive (if consumer gets the incentive) or higher by the amount of the incentive (if the seller receives the incentive).

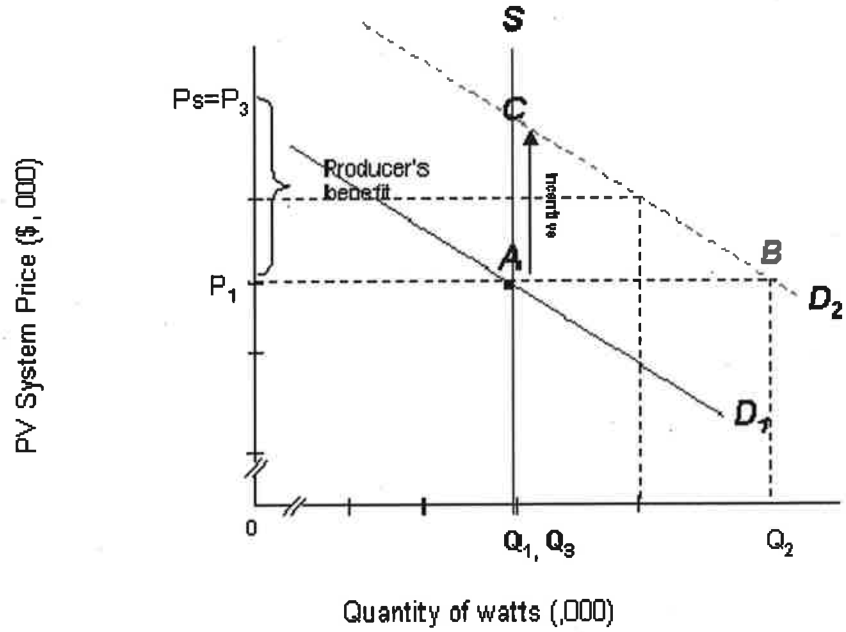
Graph 2.1: Elastic Case – Incentive Provided to Consumer



In this case, the pre-incentive equilibrium is A. An incentive to the consumer increases the willingness of the consumer to pay and shifts the demand curve up (by the incentive amount) and to the right ($D_1 \rightarrow D_2$). At the initial equilibrium price P_1, there is now an excess of demand. Consumers want Q_2 (point C) at the initial price, but sellers are only willing to sell Q_1. Consumers bid up the price as they compete for smaller quantities of watts until the new equilibrium price and quantity, *B*, are reached. P_2 is the price paid by consumers. P_3 is the sellers' price received. The new equilibrium price is higher than the initial price, but less high than the incentive amount. The consumer incentive benefit is $P_1 - P_3 +$ incentive amount. The seller incentive benefit is $P_3 - P_1 + 0$. Consumer and seller benefits total the initial incentive. In this case, the pass-through of incentives is incomplete, with approximately half flowing to the supplier.

In the long-run, it is expected that the solar PV market is elastic. Perfectly elastic supply can occur when sellers have the choice among a large number of perfect substitutes in the production. Assuming buyers shop around, any quantity of the good can be produced at the same production cost and price because the productive resources can be easily switched back and forth between other goods.

Graph 2.2: Perfectly Inelastic Supply Case – Incentive Provided to Consumer

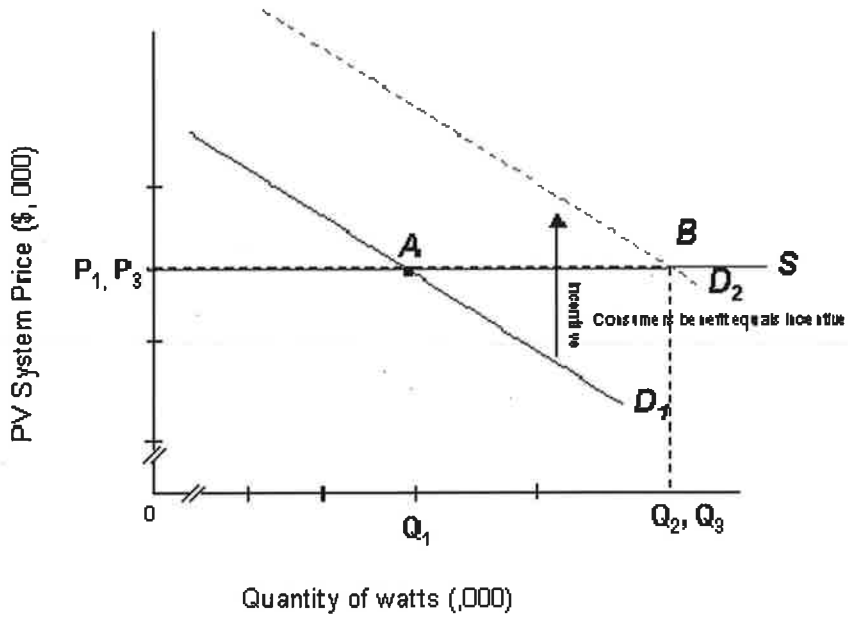


In the extreme case, supply or demand constraints, such as labor supply constraints, can lead to inelastic supply or demand and full shifting of the incentive to one party. In the more likely case of inelastic supply, the price to consumers would not decrease which would be antithetical to policymaker expectations.

In this case, the pre-incentive equilibrium is A. An incentive to the consumer increases the willingness of the consumer to pay and shifts the demand curve up (by the incentive amount) and to the right ($D_1 \rightarrow D_2$). At the initial equilibrium price P_1, there is now an excess of demand. Consumers want Q_2 at the initial price, but sellers are only willing to sell Q_3 same as Q_1. Consumers bid up the price as they compete for smaller quantities of watts until the new equilibrium price and quantity, *C*, are reached. Since supply is inelastic, the quantity supplied does not change at the new equilibrium price. P_1 is the price paid by consumers. P_3 is the suppliers' price received. The new equilibrium price is higher than the initial price by the total incentive amount.

In this case, the consumer incentive benefit is zero, $P_1 - P_3 +$ incentive amount. The seller incentive benefit is the full incentive amount, $P_3 - P_1 + 0$. Consumer and seller benefits total the initial incentive. In this case, the pass-through of incentives is zero with all of the incentive flowing to the seller.

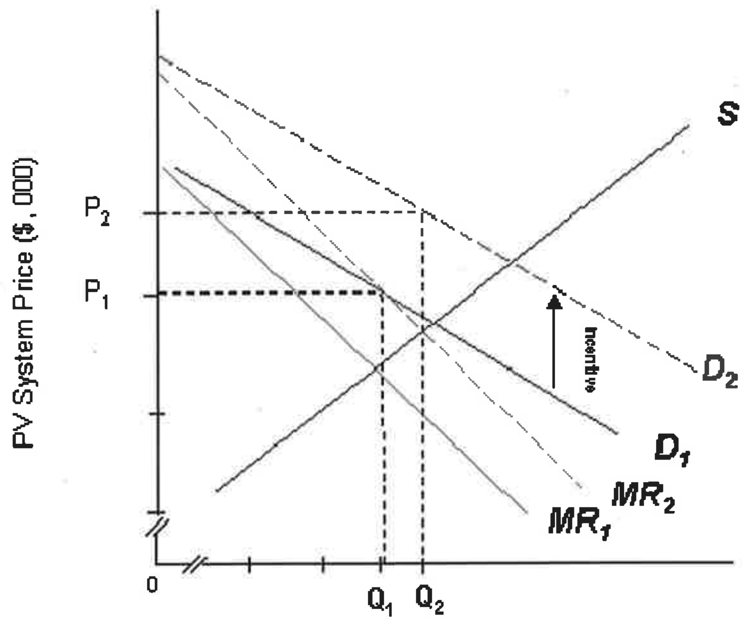
Graph 2.3: Perfectly Elastic Supply Case – Incentive Provided to Consumer



In this case, the pre-incentive equilibrium is A. An incentive to the consumer increases the willingness of the consumer to pay and shifts the demand curve up (by the incentive amount) and to the right ($D_1 \rightarrow D_2$). Consumers now want Q_2 at the initial price P_1,. Since supply is perfectly elastic, sellers are willing to sell Q_2 at the initial equilibrium price P_1. Since supply is perfectly elastic, the quantity supplied changes, but the new equilibrium price paid by consumers, P_3, does not change.
The consumer incentive benefit is the full incentive amount, $P_1 - P_3 +$ incentive amount. The seller incentive benefit is zero, $P_3 - P_1 + 0$. Consumer and seller benefits total the initial incentive. In this case, the pass-through of incentives is full, with all of the incentive flowing to the consumer.

The above models of incidence are based on competitive markets. The graph below details incidence under an extreme case of imperfect competition, a monopoly market with non-discriminating pricing. Incidence under a monopoly market is a function not only of supply and demand elasticities but of the curvature of the demand curve. In a market with monopoly power, there is only one supplier of the good. A monopolist sets marginal cost equal to marginal revenue and the price of the good is determined by the monopolist and not the market. A monopoly solar PV market is not expected in the long run, although market power could exist in the local contractor market.

Graph 2.4: Market Power – Incentive Provided to Consumer



In the monopolist case, the pre-incentive equilibrium quantity is Q_1 and is the quantity at which the marginal revenue curve, MR_1 intersects with the supply curve. The pre-incentive equilibrium price, P_1, is determined by the demand curve and is the price at which Q_1 is demanded. The monopolist charges P_1, which is above the marginal revenue curve. An incentive to the consumer increases the willingness of the consumer to pay and shifts the demand curve up (by the incentive amount) and to the right ($D_1 \rightarrow D_2$). This leads to the marginal revenue curve also shifting to the right ($MR_1 \rightarrow MR_2$). The monopolist determines the new equilibrium by once again identifies the quantity, Q_2, at which the marginal revenue curve, MR_2, intersects with the supply curve. The monopolist then sets the price at P_2, the price at which the market demands Q_2. The new equilibrium price is higher than the initial price but less than the total incentive. Similar to the elastic case (graph 2.1), the monopolist shares the incentive benefit with the consumer, although the total benefit to consumers and producers is greater than the subsidy cost because the quantity sold is already distorted downwards.

Data Overview: Incentives for Solar PV in California

This analysis uses variation in incentives within and across programs to estimate incentive pass-through. Incentives offered by programs varied across time and customer class due to rebate schedules, system size requirements, system performance adjustments, incentive type, and incentive caps. The greatest source of variation in the data is from different incentive levels offered across time and programs. This section details each incentive program's components and the additional data used in the analysis.

This paper uses 2000 to 2008 incentive and PV system data from the major California solar PV incentive programs to estimate subsidy incidence to California PV consumers.[20] The programs included are the Emerging Renewables Program (ERP), California Solar Incentive (CSI), New Solar Homes Partnership (NSHP), LADWP Solar Photovoltaic Incentive Program, and SMUD PV Program. The first three programs were primarily available only to consumers in one of the state's Investor Owned Utilities (Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric[21]). The LADWP and SMUD programs are available to consumers in their respective utility territories. Combined, these five utilities represent 90% of California's electric load during the study period. The unit of observation is a PV system (kW) (including modules, inverter, Balance-of-System parts, permitting, and labor). PV system technical, price, and installation data were collected from incentive program administrators through the Lawrence Berkeley National Laboratory's Tracking the Sun II project.

The data are limited to PV systems with similar technology and installation approach and so systems with building integrated PV, thin film or hybrid thin film, and self installs are excluded. The data are also limited to systems between 2 and 10 kW. Systems missing any of the OLS regression variables are also excluded. Before data screens, 313.2 MW were incentivized across the programs during the time period, including commercial systems and systems greater than 10 kW. After data screens, 26,465 systems remain for a total of 127.8 MW. The Emerging Renewables Program has the most systems, and in the data represents 64% of total systems installed and 63% of kilowatts installed.

[20] The initial data included observations from 1998 and 1999. However after the data were screened to exclude systems with various characteristics (noted in the data screening section) 39 observations from 1998 and 178 observations from 1999 were dropped. The most systems were dropped from the data due to estimated system size.

[21] In the beginning of the ERP Publicly Owned Utilities were eligible so the final ERP data set includes 73 POU systems.

Table 2.1

Observations by Program and Year										
Program	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**Total**
Emerging Renewables Program		2	752	1,987	3,311	2,669	4,302	3,617	249	16,889
New Home Solar Partnership								48	141	189
California Solar Initiative								2,474	5,631	8,105
LADWP Solar Incentive Program	3	51	150	167	34	63	113	258	320	1,159
SMUD Residential Retrofit Program						14	20	45	44	123
Total	3	53	902	2,154	3,345	2,746	4,435	6,442	6,385	26,465

Program and Incentives Overview

The Emerging Renewables Program (1998-2008)

The Emerging Renewables Program (ERP) was created by omnibus California restructuring legislation Assembly Bill 1890 (AB 1890) and Senate Bill (SB90). Enacted in 1996, AB1890 provided $54 million to support emerging renewable electricity generation technologies, including rooftop solar PV, small wind, and fuel cells. SB90 (1997) provided specific direction on how those funds were allocated. Additional program funding was authorized through subsequent legislation (SB 1038 (2002-2006), SB107 (2007) and SB1250 (2007)).

Distributed solar PV systems, including new homes, were funded through the ERP from 1998 to 2006 and represent over 95% of ERP incentives during the period. From program inception to February 2003, the ERP provided rebates to both small and large PV systems, but after March 2003, the program focused primarily on residential and small commercial systems under 30 kW. In 2007, PV systems for IOU consumers became exclusively funded under the California Solar Initiative and the New Solar Homes Partnership.[22] However, the ERP data include systems with completion dates through 2008.

To participate in the ERP, eligible systems were required to have a minimum five year warranty, installation by an appropriately licensed contractors (A, B, or California C-46 Solar Installer license, or C-10 Electrical Contractor license), and key PV system components certified to meet established standards.

The ERP total residential incentive varied by reservation date, incentive cap, and system performance characteristics. The initial ERP schedule set the incentive level to decline in five steps from $3 per watt to $1 per watt. Since the program had no established MW targets, each incentive level was tied to a specific portion of the program's $54 million authorization. The five blocks of funds varied in size from $10.5 to $12 million. Although the incentives were designed to decline from 1998 to 2001, all reservations received the initial incentive level established in Block 1, $3.00/W.

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[22] ERP systems in database from 2008 reflect the final completion date for remaining systems allocated under ERP (through 12/31/06). Systems not completed by January 1, 2007 had the option to withdrawal their applications from the ERP program and move to the CSI program.

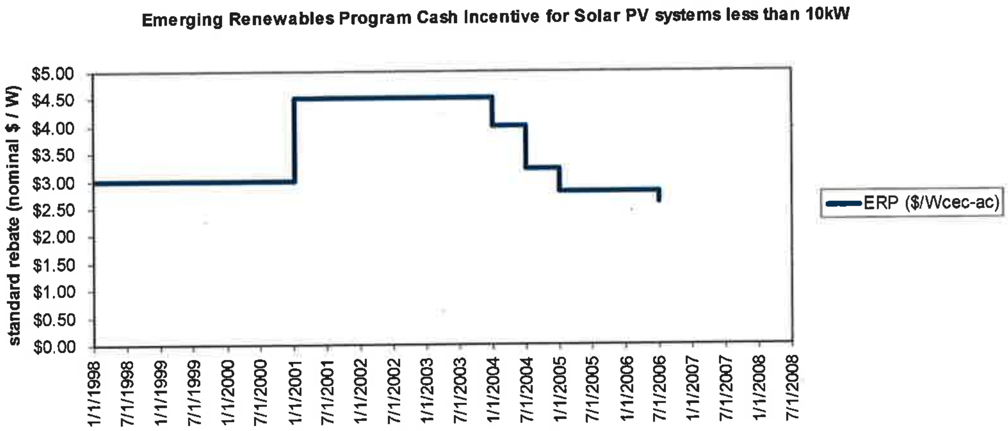
SB 1038 removed the requirement established by SB90 for declining incentives. In 2001, the ERP permanently deviated from its initial set schedule, and the incentive increased from \$3.00 per watt to \$4.50 per watt in February 2001. The decision to increase the incentive during the electricity crisis was exogenous to demand for the ERP. The subsidy was changed to be aligned with subsidy levels offered in the CPUC's Self-Generation Program (SGIP) which was established in 2001 to support larger, commercial systems.[23] PV systems were eligible for only one of the two programs. The ERP incentive remained \$4.50 per watt through December 2003 after which it declined steadily until it reached \$2.60 per watt at the end of the sample period.

Through February 2003, ERP incentives faced a cap of 50% of total eligible costs, with periods of a 40% cap for systems greater than 10 kW. 1.7% of systems in the final data faced the 50% incentive cap. After February 2003, the incentive percentage cap was eliminated. The total incentive was also capped at \$2.5 million and \$1 million during the study period; however these caps were not binding for any observations in the sample.

The total incentive the consumer received also changed with certain system performance characteristics. In the ERP, system size incentivized was adjusted downwards to reflect differences in module operation under real world performance conditions and inverter efficiency. Consumers with the same nameplate system capacity could receive different incentives depending on, for example, the inverter efficiency. The ERP incentive level also varied with incentive type, whether the system was self-installed and total system size. However these types of variation are not present in the data since self installs were excluded from the analysis and no residential systems utilized the pilot performance based incentive, which was limited to systems greater than 30kW. Although not captured in this data, the ERP also offered for a period a lower incentive for systems greater than 10kW. From 1999-2000, these larger systems received an incentive of \$2.50 per watt, a 17% lower incentive than for smaller systems.

[23] The SGIP was started at \$4.50/watt, and initially covered all PV systems, overlapping with the ERP. Overlap was reduced by limiting SGIP to systems greater than 30kW.

Graph 2.5



Incentive declined on February 8, 2001; January 1, 2004; July 1, 2004; January 1, 2005; and July 1 2006.

California Solar Initiative (2007-2016)

The California Solar Initiative (CSI) was created by California's Senate Bill 1 (SB1) in 2006. SB1 continued upfront buydown and performance based incentives first established for solar PV in the Emerging Renewables Program and Self Generation Incentive Program, but expanded the rebate program to account for differences in the new construction market, increased the utility net metering limits, and required publicly owned utilities to create their own solar rebate programs.

Under SB1, the CSI had $2.167 billion allocated for IOU solar PV consumers from 2007-2016. Administered by the California Public Utilities Commission, the CSI program has a 1,940 MW goal and funds distributed solar PV systems on existing buildings. The CSI is available to residential and non-residential systems 1kW -1MW[24], with each consumer class however having a set MW target.

The CSI total residential incentive varied depending on reservation date, cumulative installations within a utility service area, incentive type, and system performance characteristics. Under the CSI, systems less than 100kW were eligible for upfront buydown incentives based on expected performance (EPBB). Eligible systems were not subject to an incentive cap, although systems could not be sized greater than annual on-site load. CSI EPBB residential incentives, within each utility service area, declined from $2.50 per watt to $0.20 per watt over 10 steps of increasing megawatts during the course of the program. The incentive level depended on the reservation submittal date and the total solar demand (MW reserved) within a utility service area. Non-residential systems had similar incentives, but different total MWs targets for each step. Although there were 10 steps, in accordance with the CPUC policy decisions that provided for a transition between the Self Generation Incentive Program (SGIP) and CSI, step 1 was fully reserved in 2006 under the SGIP, which was only open to non-residential projects. The 50 megawatts in step 1 were not allocated across the utilities and were

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[24] CEC-AC rating, but not design factor was used to determine minimum and maximum size eligibility.

reserved on a first come, first served basis. By the end of the data sample (2008), for residential systems, SCE reached step 3, SDG&E step 4, and PG&E step 5. Although Performance Based Incentives were required for systems 100kW are greater, smaller systems could opt-in. 1.5 percent of CSI residential data observations utilized the PBI.

Table 2.2

CSI Residential MW Target by Utility			
	PG&E	SCE	SDG&E
Step			
1			
2	10.1	10.6	2.4
3	14.4	15.2	3.4
4	18.7	19.7	4.4
5	23.1	24.3	5.4
6	27.4	28.8	6.5
7	31.0	32.6	7.3
8	36.1	38.0	8.5
9	41.1	43.3	9.7
10	50.5	53.1	11.9
Total	252.4	265.6	59.5
Total % by Utility	43.7%	46.0%	10.3%

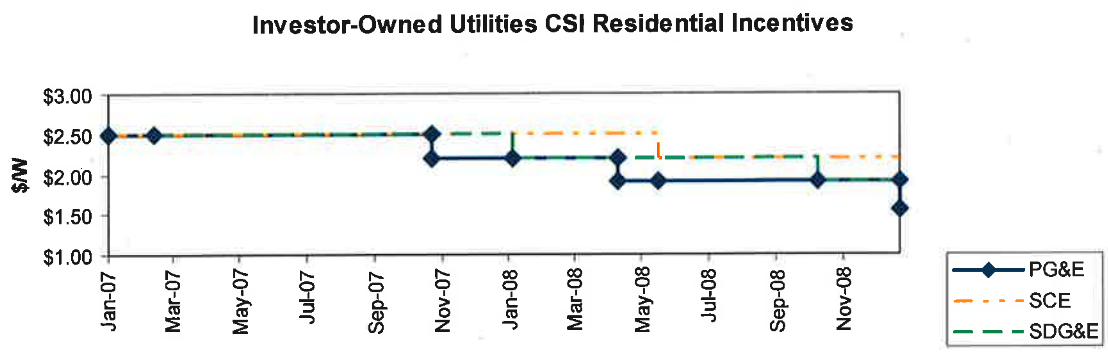
PG&E reached Step 3 October 2007, Step 4 April 2008. SCE reached Step 3 May 2008. SDG&E reached Step 3 January 2008 and Step 4 October 2008.

Table 2.3

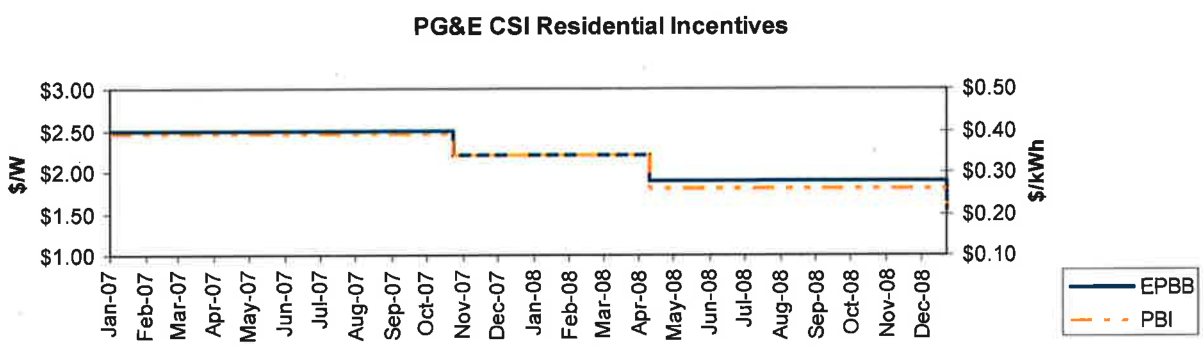
CSI Residential Incentives		
MW Step	EPBB	PBI (per kWh)
1		
2	$2.50	$0.39
3	$2.20	$0.34
4	$1.90	$0.26
5	$1.55	$0.22
6	$1.10	$0.15
7	$0.65	$0.09
8	$0.35	$0.05
9	$0.25	$0.03
10	$0.20	$0.03

Similar to the ERP, the total incentive the consumer received changed with certain system performance characteristics. Before calculating the total incentive (rebate level*system size), the CSI downwardly adjusted system size to reflect differences in module operation under real world performance conditions (DC-PTC), inverter efficiency, and design factors such as weather, shading, mounting, and tilt.

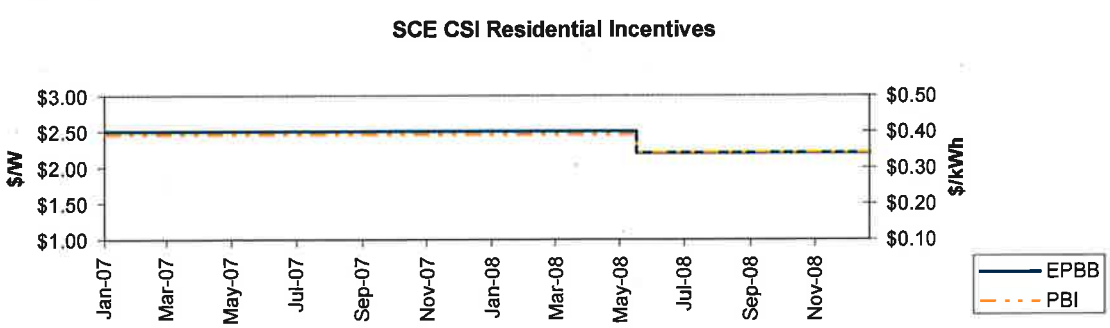
Graph 2.6



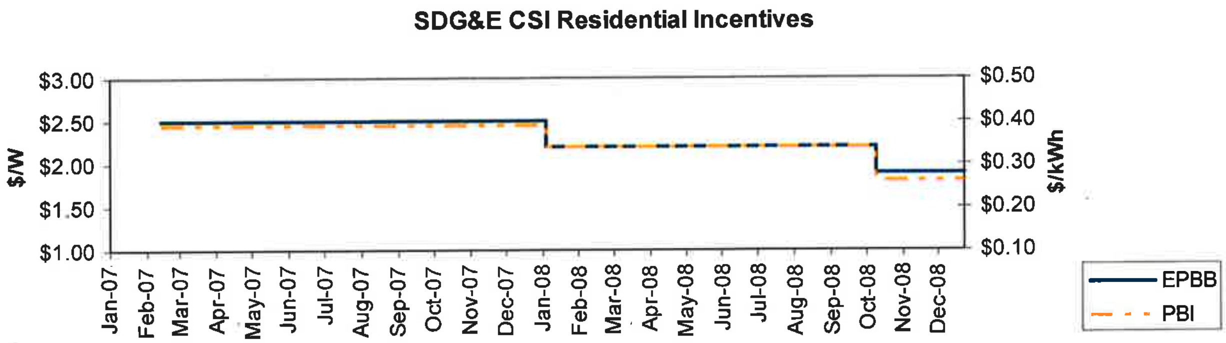
Graph 2.7



Graph 2.8



Graph 2.9



New Solar Homes Partnership (2007- Present)

The New Solar Homes Partnership (NSHP) was also created under California's Senate Bill 1 (SB1). The New Solar Homes Partnership has a total maximum budget of $400 million, with a goal of 400 megawatts of solar PV on new homes by 2016. Administered by the California Energy Commission, the NSHP incentive is an upfront incentive based on expected system performance (EPBB) and is available for market-rate and affordable housing in the state's IOU territories. Eligible systems must be at least 1 kW and cannot be sized greater than residence expected load.

During the analysis period, the NSHP total residential incentive varied depending on home type and system performance characteristics. NSHP offered a higher incentive for a reference production home with solar as a standard feature, and a lower incentive for other homes. To qualify as a reference production home with solar as a standard feature, the builder had to commit at the reservation stage that a minimum of 50 percent of the homes in a subdivision or multi-family housing development would have solar systems. The lower incentive was referred to as the base incentive and applies to custom homes, small developments, reservations where solar is identified as an option, and all applications where solar is not installed as a standard feature. In the data, 76% of incentives were for systems using solar as a standard and as such they received a higher incentive.

To determine the total incentive, the NSHP also adjusted system capacity and output to reflect system performance characteristics although it employed a different methodology. The NSHP converted the $/W incentive to a time-dependent weighted $/kWh incentive for an ideal, reference system. Unlike the CSI and ERP calculators, the NSHP rewarded expected generation that exceeds that of the reference system in the reference location. The $/kWh incentive was then multiplied by the PV system's expected kWhs (determined hourly over a year). Expected kilowatt-hours are a function of system characteristics such as module real world performance, inverter efficiency, module orientation, tilt, and type, system power losses, and geographic location. With an hourly focus, the NSHP incentive was greater optimized to address peak load, and as such NSHP systems had a greater incentive for southwest facing systems. In the CSI, incentives were more evenly distributed around the compass.

To participate in the NSHP, homes had to first meet a higher efficiency standard of 15% (Tier 1) or 35% (Tier II) beyond the energy efficiency mandated by California's Title 24 building efficiency standards. Both Tier I and Tier II systems are included in the analysis. Tier II systems did not receive an additional cash incentive although such applicants did receive additional marketing support. Tier II systems represent 80% of the final NSHP data. Exclusion of either Tier I or Tier II systems does not significantly change overall analysis results.

The NSHP incentive level was initially scheduled to decline over time by 10% in response to 10 volumetric trigger steps. However, due to slow program uptake, and program administrator concerns about declining new home construction, the incentive level did not decline during the data period. The incentive for production homes was $2.60 per watt and $2.50 per watt for other homes through 2008. In January 2012, later than the data sample, the Energy Commission issued a revised declining incentive schedule.

Publicly Owned Utility Programs (POUs): LADWP and SMUD

Publicly owned utilities represent 25% of California's electricity demand. Two utilities, Los Angeles Department of Water and Power (LADWP) and Sacramento Municipal Utilities District (SMUD), represent over 90% of publicly owned utility electricity sales. An additional 46 utilities represent the remainder of POU load.

<u>CA LADWP Solar Incentive Program (2000- Present)</u>

In response to AB1890, The Los Angeles Department of Water and Power's (LADWP) solar program began offering upfront cash buydown incentives in 2000. The program was updated in 2007 to reflect new guidelines established under SB1. Under SB1, publicly owned utilities were mandated to establish solar programs by 2008 to assist with the state's goal of 3,000 megawatts of solar by 2016. LADWP's required share of the SB1 goal was 280 megawatts. The LADWP program provided performance based incentives and maintained separate funding goals for residential and non-residential participants as well as an additional incentive for PV modules manufactured in Los Angeles.

Pre-SB1 the program had total funding of $14 million to a maximum of $22 million for both residential and non-residential systems. Since SB1, the program has an overall funding cap of $313 million through 2017, with $144 million of funding dedicated to residential systems. Funding is allowed to be less, provided that the funding is sufficient to provide an incentive of at least $2.80 per watt. The revised program is funded through a public benefits fund and $30 million is available annually.

Initially the minimum system size was 300 watts and the maximum system size 1 MW. Starting in 2007, the program had minimum and maximum system size requirements of 1 kW and 3 MW and a maximum $7 million incentive payment limit per billing meter each fiscal year. The system had to be sized to be no greater than the entire consumer load.

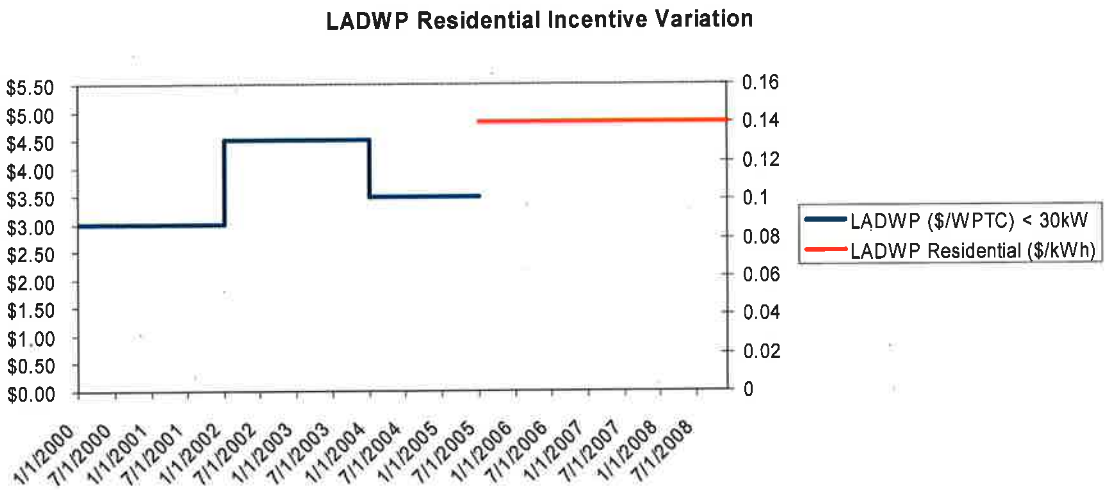
LADWP's total residential incentive varied by reservation date, incentive type, incentive cap, equipment manufacturer location, and system performance characteristics. Although initially set to decline every 12 months, the incentive level frequently varied due to continual updates and revisions to the incentive level and schedule. Prior to 2006, systems were only eligible for an upfront cash buydown incentive. The program transitioned to expected performance based incentives in 2005, and moved exclusively to performance based incentives in 2006. From 2000 through December 2001, the incentive for all systems was \$3.00 per W_{PTC} with an additional \$2.00/ per W_{PTC} incentive offered for systems manufactured by a Los Angeles company.[25] The base incentive increased to \$4.50 per W_{PTC} in 2002, declining to \$3.50 per W_{PTC} from 2004 to 2006. In 2006, a declining performance based incentive schedule based on estimated system performance, tied to volumetric triggers was introduced. In 2007, the declining incentive schedule was once again revised to ten declining block steps. The residential EPBB started at \$0.14 cents/kWh and reached the second step, \$0.13 cents/kWh in December 2008. The data does not include any observations beyond Step 1. The variation in incentive level by reservation date is depicted in graph 2.10. LADWP's program had a residential incentive cap of 85% of total installed cost through 2004 and 75% thereafter, but it is not binding for systems in the sample.

In addition to changing incentive levels, similar to the IOU programs, the total LADWP incentive provided was downwardly adjusted to reflect differences in module operation under real world performance conditions (DC-PTC), inverter efficiency, and design factors such as weather, shading, mounting type, and cell temperature. The extent to which system performance was considered in determining adjusted system size varied during the program.

From the onset, the incentive level accounted for module performance, by requiring system output to be measured using the PTC which adjusts for module efficiency. Starting in August 2004, the total incentive paid also adjusted for inverter losses and a 13% loss for wiring. The transition to performance based incentives mid-2005 changed the total incentive calculation to be based on estimated performance for 20 years. The estimated performance accounted for system tilt, orientation, shading, and installation location and a system degradation factor of 0.9.

[25] According to LADWP program administrators virtually no one received the LABC subsidy during the data period (less than 1% of applicants eligible), but the LABC incentive is not identified in the available reported data.

Graph 2.10



SMUD Residential Retrofit and Commercial PV Buydown Programs

Since 1999, SMUD has offered buydown incentives for residential and rooftop PV systems. In 2004 SMUD transitioned from a direct sales program, in which the utility sold subsidized systems to consumers, to a consumer rebate program that provided upfront cash incentives. After the passage of SB1, SMUD offered both expected performance based buydown incentives (EPBB) and performance based incentives for grid-connected PV to residential and commercial consumers. SMUD's required share of the SB1 goal was 125 MW. The program had no caps on system size or incentives, but did require systems to be sized not to exceed consumer's annual consumption. Starting in 2007, systems installed by NABCEP certified installers received an additional $200 incentive for the contractor. The relatively small size and limited use of this additional incentive, however, resulted in this contractor incentive not being isolated in the analysis from the overall after-tax cash incentive. Incentives were available on a first come, first serve basis.

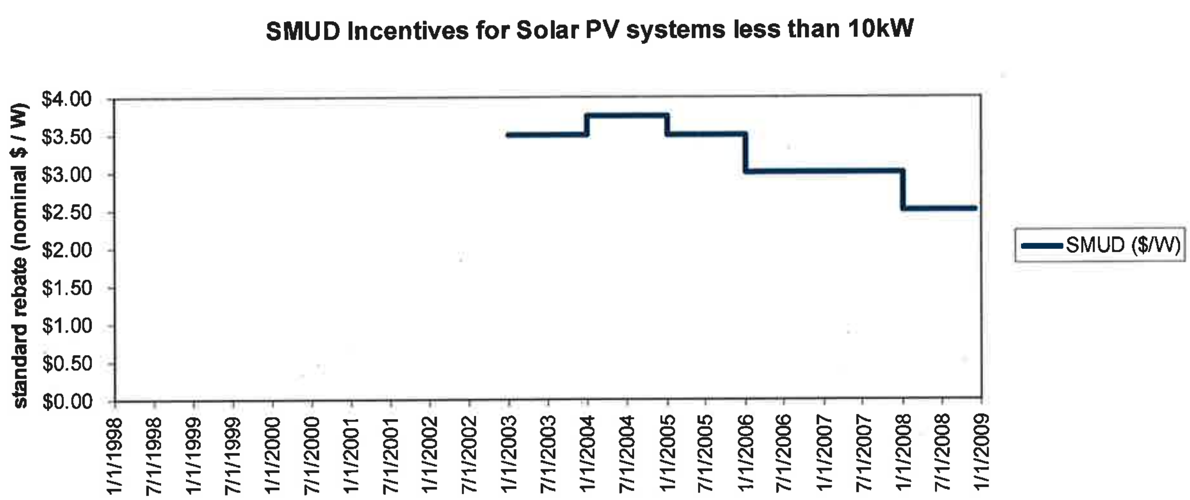
SMUD's total residential incentive varied by reservation date, incentive type, and system performance characteristics. In 2005 and 2006, SMUD offered a $3.50 per watt and $3.00 per watt EPBB incentive respectively. Starting in 2007, a ten step, declining incentive schedule was established and consumers were eligible for an EPBB or PBI incentive. The PBI was the sole option for systems installed under third-party PPAs and lease options. The PBI was designed so that the net present value of the sum of the payments was equal to the current EPBB level adjusted by a 7.5% annual discount rate and 0.05% per year system output degradation. The incentive level reached Step 2 ($2.50) during the data sample.

In addition to changing incentive levels, similar to the IOU programs, the total incentive provided was downwardly adjusted to reflect differences in module operation under real world performance conditions (DC-PTC), inverter efficiency, and design factors such as shading, tilting, mounting method, and orientation. The additional factor of system degradation (0.05% a year) was added in 2007.

Table 2.4

SMUD 10 Residential Incentives Steps (per Watt)	
MW Step	EPBB
1	$3.00
2	$2.50
3	$2.20
4	$1.90
5	$1.55
6	$1.10
7	$0.65
8	$0.35
9	$0.25
10	$0.20

Graph 2.11



Tax Credits and other non-cash subsidies for Solar PV

In addition to these rebate programs, through 2008, other policies supporting PV in California included: state and federal tax credits, net metering requirements, simplified interconnection standards, and an exemption of PV systems from state property taxes. Net metering allowed PV customers to credit excess generation at the retail rate to their next billing cycle. California systems, except for systems within the LADWP service territory, have been eligible for net metering since 1996.

The availability and size of the tax credit depended on the market segment, system size, and year. The state tax credit cap of $4.50 per Watt_{ac} was not binding for any observations in the sample. The federal tax credit cap of $2,000 was binding for nearly all systems. About 1% of the systems eligible for a residential federal tax incentive had a tax credit lower than the cap. Table 2.5 describes the tax credits available.

Table 2.5

State and Federal Solar PV Investment Tax Credits				
Tax Credit	**Customers**	**Period**	**Credit Level**	**Incentive Cap**
CA State ITC	All	2001-2003	15% of post-rebate installed cost	$4.50/$W_{AC}$
CA State ITC	All	2004-2005	7.5% of post-rebate installed cost	$4.50/$W_{AC}$
Federal ITC	Commercial	1998-2005	10% pre-rebate installed cost	None
Federal ITC	Commercial	2005-2016	30% pre-rebate installed cost	None
Federal ITC	Residential	2006-2008	30% post-rebate installed cost	$2,000
Federal ITC	Residential	2009-2016	30% post-rebate installed cost	None

Since Federal tax incentive and state incentive data were not available, the Federal ITC and State ITC were estimated for systems. Projects in the data identified as residential PV and installed on or after January 1, 2006 were assumed to receive a Federal ITC equal to the lesser of 30% of the tax credit basis or $2,000. However, the tax credit estimates produced nonsensical results in the regression analysis and so are not included in the final analysis. Instead pass-through is calculated using only the after tax cash incentive.

Subsidy Variation Conclusion

As detailed, the incentives within and across programs varied due to system size, system performance adjustments, time of purchase, total eligible costs, incentive type, and incentive caps. Incentives were offered on a per Watt basis and the total incentive received by each system equals the system size times the appropriate rebate level (subject to any incentive caps). However, given that the data for this analysis is restricted to residential systems from 2000-2008, the primary source of variation in incentive levels is across time and within and across programs.

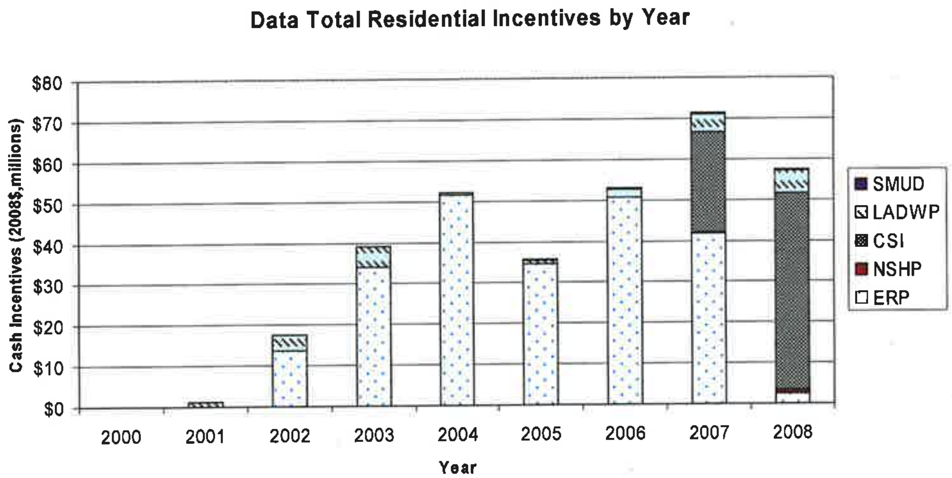
For the ERP, incentives varied across time, in fact they changed five times during the data period. Incentive for the ERP also varies due to the incentive cap of 50% of total costs. 1.7% of ERP systems completed in 2002-2007 faced the cap.

For the CSI, incentives varied across time and utility. Although the incentives started at the same level for each utility, during the study period they declined twice for PG&E's and SDG&E's territory and once for SCE's territory. These incentive declines occurred on different dates across the utilities.

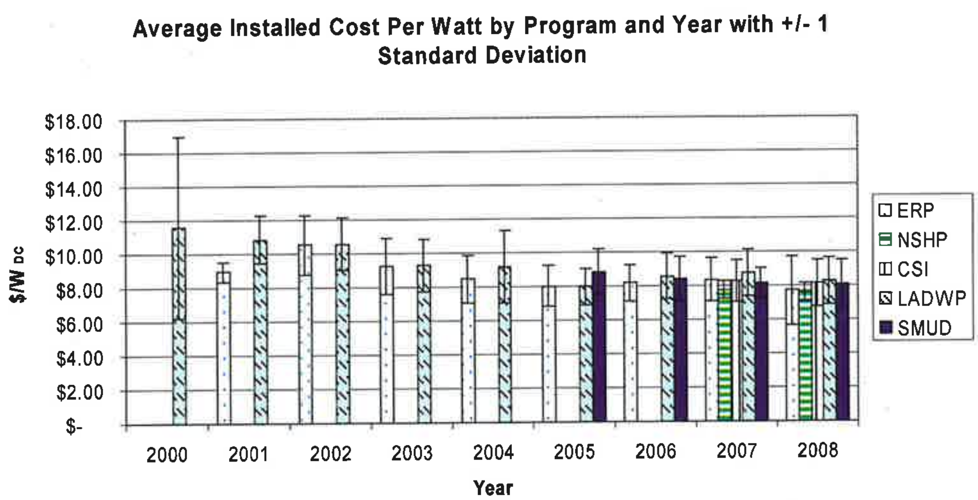
For the NSHP, there is 10 cents per Watt difference in incentives between homes with solar as standard and other homes. 76% of NSHP systems in sample received the higher incentive. Otherwise the incentives do not vary during the sample time period.

For LADWP, the incentive changed over time with an increase in 2002 and a decrease in 2004. For SMUD, the incentive level increased once and decreased twice during the sample period.

Graph 2.12



Graph 2.13



Other Key Price Drivers

Total system capacity (kW) is the primary determinant of net price, the total price minus the incentive, and is a key component of this analysis. The larger the system's generating capacity, the more expensive the overall PV system. PV systems are modular in nature and priced accordingly. Dong, Wiser, and Rai (2014) find some economies of scale due to system size and the Lawrence Berkeley National Laboratory Tracking the Sun reports find evidence of economies of scale in systems less than 5 kW. For this analysis system capacity is measured as the standardized module nameplate capacity rating ($W_{DC\text{-}STC}$) times the number of modules in a PV system. System capacity is reported in kilowatts for ease of review. Industry practice is to use $W_{DC\text{-}STC}$ when selling modules and it is a comparable metric across module models.

This nameplate system size is used for this analysis because it captures the system sizing and module pricing factors that influence net price that are commonly reported to the program administrators. Although modules have differing real world performance and at times incentives were adjusted for performance, modules were not significantly differently priced based on these performance factors. Remaining cost competitive remained the primary pricing driver for module manufacturers. Despite the very real differences between certain brands (within a single technology class), pricing is fairly homogenous during this period with regards to module performance. Anecdotal evidence also suggests that consumers, in particular residential and commercial consumers with smaller system sizes, did not assign extra willingness to pay on production benefits. For such consumers, minor adjustments became less important in absolute terms and consumers relied on simpler metrics such as $/W. The impact of performance adjusted system size on net price may increase as programs moved towards performance based incentives that account more for such performance differences in the incentive amount. This analysis was conducted using both nameplate and performance adjusted system ratings and the difference in incentive pass-through was not statistically different.

Contractor quality, as measured by installation experience, can also influence net price. Experience, as well as contractor training and certification, can lower costs by increasing human productivity through such mechanisms as inter-project learning and establishment of a common code of language that facilitates knowledge spillovers. (Becker, 1975; Shum & Watanabe, 2007; Shum & Watanabe, 2008). Such factors however may also lead to an increase in prices if they result in superior installer quality that is signaled to the market through higher prices (Spence, 1973). Empirical evidence also exists that professional status, through education and certification, offers a path to higher wages (Garud and Karnoe 2001). Analysis of California PV system prices found mixed results for contractor experience. Gillingham et al. (2014) and Dong, Wiser, and Rai (2014) find contractor experience and increased installer density lower net prices paid by consumers. Earlier analysis, (Wiser, Bolinger et al., 2006), finds that experienced installers in the ERP, identified as the top 5% of contractors by aggregate installations in the program, charged more than less experience installers, but that experienced installers in the California Public Utilities Commission SGIP program charged less for systems (Wiser, Bolinger et al., 2006).

For this analysis, cumulative contractor experience is calculated using all California PV system data available, prior to data screens. The pre-screened data includes

42,497 observations and eight California solar PV programs. In the final data contractor experience is mixed and diverse. 1,247 contractors installed the 26,465 systems. After the other screens, 217 systems were excluded since installed by the homeowner themselves. For this analysis I limit contractor experience to experience within a given county. The average installer cumulative county experience for an installation in the data is 156 kW. This limitation is reasonable since contractor teams and permitting are local, or at least sub-national, even if part of a national or international company. Gillingham et al. (2014); Dong, Rai, Wiser (2014); Henwood (2014); and Davidson and Steinberg (2014) also measure experience at the county level. I also interact the final contractor experience variable, *Experience*, measured in kilowatts, with system capacity, *kW* because I expect the effect of experience to change proportionally with system size.

Market structure characteristics, such as *market concentration*, can increase or decrease installation costs and price. Due to economies of scale, increased market size should lower net price if installers are price-takers in a competitive market. However, if market concentration exists, and market power is exercised, firms can extract a higher price from consumers (Viscusi, Joseph E. Harrington et al., 2005). Anecdotal and empirical evidence suggests that California PV markets are not perfectly competitive and there is variation in competitiveness across the counties. In this analysis the Herfindahl–Hirschman Index (HHI), measured at the county level in a given year, is used as a measure of market power. The HHI is the sum of the squares of the market shares of the PV contractors installing solar PV incentivized by the eight California programs for which data is available.[26] HHI is calculated using all California PV system data available, prior to data screens. The pre-screened data includes 42,375 observations (less than the cumulative experience variable because some observations were missing county identification). As with contractor experience, county is chosen as the market definition.

The inclusion of all PV systems incentivized under California programs may downwardly bias the market power calculation because this wider net includes commercial and larger contractors who may not participate in the residential solar PV market. However, a number of firms do participate in both the residential and commercial markets and so exclusion of these systems could potentially overestimate market concentration. Using whole percentages, HHI can range from zero to 10,000 with zero representing perfect competition and 10,000 representing full monopoly market power. A HHI greater than 2,500 is considered by the U.S. Department of Justice and federal agencies as a high concentration. The Department of Justice generally considers a HHI between 1,500 and 2,500 as moderately concentrated. In the data, 54 counties are represented and average HHI is 1,187 which suggests, that on average, the markets are not concentrated. However, some higher concentration county years exist. 1511 PV systems (5.7%) are installed in market years with HHI greater than 2,500 (5.7% of the sample). 342 of the PV systems (1.3%) are in markets with HHI greater than 5,000, and 39 systems (0.1%) are installed in market years with 100% market concentration (HHI equal to 10,000). Not surprisingly, the 9 counties with HHI in a given year equal to 10,000 are smaller and more rural counties, including Colusa, Fremont, Glenn, Imperial,

[26] In addition to 5 CA programs in the study the HHI calculation also includes data from the CA Anaheim Solar Advantage Program, the CA Lompoc PV Rebate Program, and SGIP program.

Inyo, Lassen, Mono, San Benito, and Stanislaus counties. One would expect there to be a smaller number of PV contractors, and as such less competition in these markets. In the analysis, the final market power variable, *HHI*, measured at the county level, is interacted with PV system capacity because the effect of market power is expected to change proportionally with system size.

Consumers' willingness to pay for solar PV can also lead to higher net prices and less incentive pass-through. If a contractor has market power and is able to identify the maximum price a consumer is willing to pay for solar PV she can extract higher rents. Household income is a primary and positively correlated factor with a consumer's willingness to pay for green electricity and other green products. Additional key drivers of willingness to pay include education and environmental attitudes. Studies have found a consumer premium, but not a large one for green products (Batley et al., 2000, Bollino, 2009, Faiers & Neame, 2006, Scarpa & Willis, 2010, Yoo & Kwak, 2009, Zarnikau, 2003, and Zoric and Hrovatin, 2012). Less price sensitive, higher income households may also have lower pass-through of incentives if wealthier consumers engage in less search activity for lower prices. Instead such consumers may rely on other factors such as neighbor recommendations to select a contractor. Notably, solar PV consumers have a higher income distribution than the general population so I hypothesize that the wealthiest PV consumers have less incentive to be price sensitive. Henwood (2014) finds that consumers in zip codes in the bottom quartile have a pass-through rate of approximately 14 percentage points higher than zip codes in the highest quartile of his 2007-2012 California solar PV data which supports this hypothesis. Since household level income data are not available in my self-reported dataset, median household income at the zip code level (*Income*) from the 1999 census is used for this analysis.

Electricity consumption is another indicator of willingness to pay since larger consumers, especially consumers facing an increasing tiered rate price structure (the majority of the sample), have a greater economic incentive to install solar PV. Electricity consumption data are not available, and as such this driver is excluded from the analysis. In the analysis, *Income*, is interacted with the PV system capacity because I expect the effect of income to change proportionally with system size.

Data Screening

To avoid excessive influence of outliers and to eliminate data errors, the following types of systems are screened from the data: systems with missing data, installed price less than $\$3/W_{DC\text{-}STC}$, installed price > $\$30/_{DC\text{-}STC}$, systems less than 2 kW and systems greater than 10 kW, price net of subsidy less than zero, battery-operated systems, thin-film or hybrid technologies, building integrated photovoltaics, consumer segments commercial, government, and non-profit, systems with estimated system capacity, affordable housing, and self-installs. For observations with consumer segment not known, it is assumed that systems less than or equal to 10kW are residential. In the two-stage least squares estimation, further eliminated are systems with roof square footage per watt greater than 50 and building square footage greater than 20,000 square feet. The data, after screening, contain 26,465 systems, installed from 2000-2008, totaling 127.8 MW.

Table 2.6 provides data summary statistics. The average system size is 4.6 killowatts and the average installation year is 2006. Systems have an average total price of $26,079 with an average of 32% of total price offset by available program incentives.

Table 2.6

All California Regression Variables Summary Statistics				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Net Price	$26,079.4	$11,892.7	$2.3	$123,083.6
Cash Incentive	$12,250.6	$6,445.4	$935.3	$59,617.2
kW (system size)	4.6	1.9	2.0	10.0
Install Year	2006	2	2000	2008
Contractor HHI-County	1,187.4	900.0	353.8	10,000.0
Median HH Income Zip Code (,000)	$61.6	$25.1	$9.6	$200.0
Installer Experience kW	156.3	345.8	2.0	4,364.1

Dataset includes 26,465 observations

Table 2.7

Variable Correlations						
	Net Price	Total Incentive	kW (system size)	Contractor HHI-County	Median HH Income Zip Code (,000)	Installer Experience kW
Net Price	1.00					
Cash Incentive	0.49	1.00				
kW (system size)	0.83	0.75	1.00			
Contractor HHI-County	0.01	-0.05	0.01	1.00		
Median HH Income Zip Code (,000)	0.07	-0.02	0.02	-0.13	1.00	
Installer Experience kW	0.07	-0.12	0.03	0.02	0.08	1.00

Estimation Approach

A partial equilibrium model is used to estimate the incidence of after-tax solar PV incentives. Partial equilibrium analysis examines the effects of the policy action in creating equilibrium only in that particular sector or market which is directly affected. The linear specification below was chosen because net price is expected to change linearly with the incentive. Variables expected to have a proportional impact such as household income, market power, and contractor experience are interacted with system capacity.

It is assumed that the data generating process for the price, net of incentives, of an individual solar PV system is as follows:

$$NetPrice_{it} = \beta_1 + \beta_2 Incentive_{it} + \beta_3 KW_{it} + \beta_4 HHI_{it} + \beta_5 Income_{itz} + \beta_6 Experience_{it} + \beta_7 HHI*KW_{it} + \beta_8 Income*KW_{itz} + \beta_9 Experience*KW_{it} + \beta_{10} KWsq_{it} + \beta_{11} HHI*KWsq_{it} + \beta_{12} Income*KWsq_{itz} + \beta_{13} Experience*KWsq_{it} + u_t + \lambda_{z+}\ \theta_u + \varepsilon_{itzu}$$

where the dependent variable, *NetPrice,* is the PV system (with installation) total price minus the cash incentive. *Incentive*, the variable of interest, is the after-tax program subsidy awarded to a PV consumer. B_2 is the dollar change in the total system price, net of incentives, when the incentive increases by one dollar. Under most scenarios $-1 \leq B_2 \leq 0$. There are some cases, cases with imperfect competition, in which B_2 can be greater than zero or less than -1. I expect incentive pass-through to be incomplete, $-1 < B_2 < 0$. This analysis test the hypothesis that pass-through is fully incomplete; $B_2 = 0$. I also test for whether pass-through is 100% ($B_2 = -1$). The constant term allows for a non-linear relationship between system size and price.

KW is the PV system capacity in kilowatts. Market concentration, experience, and income variables (*HHI, Experience, and Income*) are included standalone and interacted with kilowatts and kilowatts squared because the magnitude of the effect of these factors is likely to be proportional to system size. Installation year (u_t), utility (θ_u), and zip code (λ_z) dummies capture time, location, and regulatory varying price shifters. The standard errors are clustered at the zip code level to account for correlation that might exist among neighbors and households facing similar local conditions. All price and cost data are expressed in 2008 dollars.

Endogeneity Concerns: Two-stage least squares estimation

Accurate estimation of the relationship between PV system prices and incentives using the above equation assumes that there is no simultaneity bias present. Such bias is possible if net price is jointly determined with at least one of the model's explanatory variables. In this model net price and system capacity (*KW*) could be jointly determined. Under certain conditions, system price could be a function of system size if a consumer selects bigger system sizes because the per-unit price is less due to the presence of economies of scale.

This type of endogeneity, consumers increasing the system size to benefit from lower unit costs, is not expected to be pronounced in this sample for the following reasons. First, under the programs, PV consumers have restrictions on the extent to which they can use or profit from excess generation. Net metering allows residential consumers to bank excess generation against their future utility electricity purchases, but only through the calendar year. Program rules also required that systems not be sized greater than onsite load and that applicants submit proof of twelve months of historical electricity usage. Finally, all of the programs have a cap on system size, and a smaller cap on system size eligible for incentives. These temporal and program conditions reduce the economic incentive for larger sized systems. Gillingham et al. (2014) decline to address this potential endogeneity in their analysis based on their understanding that system sizing decisions are nearly always based on electricity consumption and roof size. However, going forward, as policies, such as feed-in-tariffs, that allow residential consumers to export more power are adopted and as customer-sited battery storage increases in popularity, the economic rationale to oversize systems will increase. In fact, Barbose and Dargouth (2015) note that the size of residential solar PV systems has grown steadily from a median size of 2.4 kW in 1998 to 6.2 kW in 2014.

As such, although I am not particularly concerned about endogeneity for the time period under review, I still test for the presence of endogeneity using a two-stage-least squares estimation with roof size as an instrument. Roof square footage is the size of the roof of the home on which the solar PV is installed. Roof square footage is calculated based on known home square footage and the number of building stories. These data were confidentially obtained from a real estate marketing firm for a sample of the overall data set. Roof square footage is not directly available and is calculated as total square footage divided by the number of building stories from address and realtor firm data. This instrument is available for only a subset of the ERP, CSI, and NSHP. Total systems in sub-sample are 14,889, which represents 56% of the data used for the primary analysis.

Roof square footage was selected as an instrument since it reasonably satisfies both conditions of an instrumental variable:

(1) Correlation with endogenous variable system size (*KW*).
(2) Instrument is not correlated with the error term of a regression of net price on all exogenous variables.

Roof square footage is positively correlated with system size (ρ =.29). As a home's roof size increases so does the installed system size. In order to satisfy Condition 2, a factor so far omitted from the analysis, electricity consumption needs to be controlled for. Electricity consumption can be a determinant of PV system price because consumers with higher electricity consumption and higher marginal electricity rates will have a greater economic benefit from PV and a higher willingness to pay. Roof square footage is likely correlated with electricity consumption since larger footprint buildings are positively correlated with electricity consumption. However, due to lack of data, electricity consumption is not included in the model. Household square footage is available for a subset of the data and is used as a proxy for electricity consumption. Although square footage does not reflect all the determinants of electricity consumption (e.g. does not reflect number of people and usage habits), it does capture the elements of roof square footage (e.g. building physical footprint) correlated with electricity consumption. In addition to roof square footage, the number of rooms in a property is also tested as an instrument, but dropped due to poor fit. Conditioning on building square footage, roof square footage now satisfies the second 2SLS condition.

The primary specification also includes other covariates that may be endogenous since they are interacted with system size. As noted in the other key drivers discussion, these variables, *HHI, income, and contractor experience*, are expected to change proportionally with system capacity. As such, these variables also must be instrumented with roof size. The final two-stage-least-squares includes eight instruments; *roof square footage, roof square footage squared, HHI * roof square footage, HHI * roof square footage squared, income * roof square footage, income * roof square footage squared, contractor experience * roof square footage, and contractor experience * roof square footage.* The summary statistics for the two-stage-least squares regression are in Tables 2.8 and 2.9. The first stage results for all the endogenous variables are below Tables 2.10-2.17.

Table 2.8

Two-Stage-Least Squares Regression Variables Summary Statistics				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Net price	$25,726.4	$160,277.0	$547.7	$123,083.6
Cash Incentive	$11,795.0	$5,868.2	$935.3	$43,774.9
kW (system size)	4.6	1.9	2.0	10.0
Install Year	2006	2	2001	2008
Contractor HHI-County	1,071.5	715.6	358.0	7,222.2
Median HH Income Zip Code (,000)	$65.4	$26.0	$16.3	$200.0
Contractor Experience kW	168.4	320.4	2.0	434.1
Square Footage (100s)	2,376.0	9.9	4.8	167.0
Roof Square Footage (100s)	18.7	8.3	2.7	167.0

Dataset includes 14,899 observations.

Table 2.9

Two-Stage-Least Squares Observations by Program and Year									
Program	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**Total**
Emerging Renewables Program	2	414	1,131	1,812	1,510	2,503	2,144	136	9,652
New Home Solar Partnership							27	84	111
California Solar Initiative							1,604	3,532	5,136
Total	2	414	1,131	1,812	1,510	2,503	3,775	3,752	14,899

Table 2.10

First Stage Results: System Size (kW)				
Instrument	**Co-efficient**	**Robust Standard Error**	**t statistic**	**P >(t)**
F-Test = 8.36				
roofsqft (100s) - instrument	0.00920	0.00593	1.55	0.12
roofsqft squared (100s) - instrument	-.0001696	0.00013	-1.29	0.20
Contractor HHI County *roofsqft	0.00000	0.00000	0.19	0.85
Contractor HHI County *roofsqft squared	0.00000	0.00000	0.19	0.85
Median Household Income * roofsqft	-0.00003	0.00005	-0.65	0.52
Median Household Income *roofsqft squared	0.00000	0.00000	0.57	0.57
Contractor Experience * roofsqft	0.00001	0.00001	2.35	0.02
Contractor Experience * roofsqft squared	0.00000	0.00000	-0.40	0.69

Table 2.11

First Stage Results: System Size (kW squared)				
Instrument	Co-efficient	Robust Standard Error	t statistic	P >(t)
F-Test = 5.01				
roofsqft (100s) - instrument	0.03172	0.07396	0.43	0.67
roofsqft squared (100s) - instrument	-.0003455	0.00156	-0.22	0.83
Contractor HHI County *roofsqft	0.00004	0.00005	0.82	0.41
Contractor HHI County *roofsqft squared	0.00000	0.00000	-0.49	0.63
Median Household Income * roofsqft	-0.00058	0.00059	-0.98	0.33
Median Household Income *roofsqft squared	0.00001	0.00001	0.93	0.35
Contractor Experience * roofsqft	.0001694	0.00006	2.88	0.00
Contractor Experience * roofsqft squared	0.00000	0.00000	-0.99	0.32

Table 2.12

First Stage Results: System Size (HHI * kW)				
Instrument	Co-efficient	Robust Standard Error	t statistic	P >(t)
F-Test = 52.38				
roofsqft (100s) - instrument	-46.07422	22.06926	-2.09	0.04
roofsqft squared (100s) - instrument	-.1703084	0.35693	-0.48	0.63
Contractor HHI County *roofsqft	0.03730	0.02141	1.74	0.08
Contractor HHI County *roofsqft squared	0.00019	0.00034	0.56	0.58
Median Household Income * roofsqft	.1093432	0.09816	1.11	0.27
Median Household Income *roofsqft squared	-.0009016	0.00124	-0.73	0.47
Contractor Experience * roofsqft	.026531	0.00940	2.82	0.01
Contractor Experience * roofsqft squared	-0.00031	0.00018	-1.79	0.07

Table 2.13

First Stage Results: System Size (HHI* kW squared)				
Instrument	Co-efficient	Robust Standard Error	t statistic	P >(t)
F-Test = 42.92				
roofsqft (100s) - instrument	-540.77140	248.65480	-2.17	0.03
roofsqft squared (100s) - instrument	-.4387812	3.92538	-0.11	0.91
Contractor HHI County *roofsqft	0.43816	0.23923	1.83	0.07
Contractor HHI County *roofsqft squared	0.00103	0.00372	0.28	0.78
Median Household Income * roofsqft	.6703046	1.09614	0.61	0.54
Median Household Income *roofsqft squared	-.0040235	0.01354	-0.30	0.77
Contractor Experience * roofsqft	.3108096	0.10390	2.99	0.00
Contractor Experience * roofsqft squared	-.0038362	0.00191	-2.00	0.05

Table 2.14

First Stage Results: System Size (Median Household Income* kW)				
Instrument	Co-efficient	Robust Standard Error	t statistic	P >(t)
F-Test = 75.29				
roofsqft (100s) - instrument	-5.02998	0.59109	-8.51	0.00
roofsqft squared (100s) - instrument	0193617	0.01095	1.77	0.08
Contractor HHI County *roofsqft	0.00034	0.00036	0.93	0.35
Contractor HHI County *roofsqft squared	0.00000	0.00001	-0.49	0.63
Median Household Income * roofsqft	.0802992	0.00560	14.33	0.00
Median Household Income *roofsqft squared	-.0004554	0.00005	-8.35	0.00
Contractor Experience * roofsqft	.0001157	0.00053	0.22	0.83
Contractor Experience * roofsqft squared	0.00001	0.00001	1.00	0.32

Table 2.15

First Stage Results: System Size (Median Household Income* kW squared)				
Instrument	Co-efficient	Robust Standard Error	t statistic	P >(t)
F-Test = 58.78				
roofsqft (100s) - instrument	-56.92379	6.96941	-8.17	0.00
roofsqft squared (100s) - instrument	.2791657	0.12201	2.29	0.02
Contractor HHI County *roofsqft	0.00555	0.00400	1.39	0.17
Contractor HHI County *roofsqft squared	-.0000837	0.00010	-0.86	0.39
Median Household Income * roofsqft	.8307062	0.07016	11.84	0.00
Median Household Income *roofsqft squared	-0.00446	0.00057	-7.87	0.00
Contractor Experience * roofsqft	.0047231	0.00606	0.78	0.44
Contractor Experience * roofsqft squared	.0000428	0.00009	0.47	0.64

Table 2.16

First Stage Results: System Size (Contractor Experience * kW)				
Instrument	Co-efficient	Robust Standard Error	t statistic	P >(t)
F-Test = 170.51				
roofsqft (100s) - instrument	-17.11226	5.06975	-3.38	0.00
roofsqft squared (100s) - instrument	.1499844	0.10779	1.39	0.16
Contractor HHI County *roofsqft	0.00088	0.00290	0.30	0.76
Contractor HHI County *roofsqft squared	-.0000366	0.00006	-0.66	0.51
Median Household Income * roofsqft	-.0223142	0.06414	-0.35	0.73
Median Household Income *roofsqft squared	0.00038	0.00128	0.30	0.77
Contractor Experience * roofsqft	.0935572	0.01291	7.25	0.00
Contractor Experience * roofsqft squared	-.0006291	0.00021	-2.99	0.00

Table 2.17

First Stage Results: System Size (Contractor Experience * kW squared)				
Instrument	**Co-efficient**	**Robust Standard Error**	**t statistic**	**P >(t)**
F-Test = 158.34				
roofsqft (100s) - instrument	-181.3765	58.12664	-3.12	0.00
roofsqft squared (100s) - instrument	1.710182	1.24493	1.37	0.17
Contractor HHI County *roofsqft	0.01432	0.03380	0.42	0.67
Contractor HHI County *roofsqft squared	-.000537	0.00065	-0.83	0.41
Median Household Income * roofsqft	-.395618	0.71531	-0.55	0.58
Median Household Income *roofsqft squared	0.00695	0.01430	0.49	0.63
Contractor Experience * roofsqft	1.001641	0.14341	6.98	0.00
Contractor Experience * roofsqft squared	-.0069216	0.00240	-2.88	0.00

Two-Stage-Least Square Results

Table 2.18 below presents the OLS and 2SLS results for regression of net price on the set of covariates for the observations with square footage and roof square footage available.

Table 2.18

Two-Stage Least Squares Regression Results		
	(1)	(2)
	OLS	2SLS
Dependent variable: Net Price (PV system total price - cash incentive)		
After-tax cash incentive	-0.43***	-0.81
	(0.05)	(8.01)
kW (system size)	5799.58***	5463.63
	(631.90)	(14510.52)
Contractor HHI-County	-0.34	41.95
	(0.62)	(155.32)
Median HH Income Zip (,000)	-72.34***	-683.71
	(19.42)	(3794.38)
Installer Experience (kW)	1.40	-16.97
	(1.09)	(35.13)
kW Squared (system size squared)	-13.12	39.79
	(62.71)	(1841.61)
Contractor HHI-County *kW	-0.12	-18.62
	(0.24)	(38.63)
Contractor HHI-County *kW squared	0.02	1.76
	(0.02)	(3.50)
Median HH Income Zip (,000) *kW	10.19	232.42
	(8.45)	(1770.09)
Median HH Income Zip (,000) *kW squared	-0.17	-20.06
	(0.83)	(166.72)
Installer Experience (kW) * kW	-0.25	7.92
	(0.45)	(184.28)
Installer Experience (kW) * kW squared	0.02	-0.77
	(0.04)	(18.02)
Sq. Footage (100s)	38.54***	35.63
	(8.54)	(78.22)
Constant	6549.90***	17660.13
	(2001.13)	(54820.79)
Observations	14899	14899
Adjusted R-squared	0.757	0.507

Includes completion year, utility, and zip code dummies.
Includes robust and zip code-clustered errors.
All dollar values in 2008 U.S. dollars.

In the first stage, the instruments for kW and kW squared are not significant (As noted in Table 2.10, kW t=1.55 and kW squared t=-1.69). In the OLS (Model 1) the coefficient on *INCENTIVE* is negative, suggesting, as expected, that an increase in the incentive reduces the net price to the system buyer. Although the OLS estimate is significantly different from zero and -1 at the .05 level, the 2SLS variable of interest is imprecisely estimated and the hypothesis that B_2 is equal to zero or -1 cannot be rejected. The variation in instrument performance and variance in the 2SLS estimate suggests that measuring endogeneity will be challenging, However to test for endogeneity, I conduct the Hausman test comparing the OLS and 2SLS results above. The Hausman test is essentially a test of whether the loss in efficiency is worth removing the bias and inconsistency of the OLS estimators. The null is that the two estimation methods should yield coefficients that are similar. The Hausman test produces an F-statistic of 3.27, suggesting I cannot reject the null that the two estimations should yield similar coefficients. Roof square footage is highly correlated with building square footage (.81) and so its effect on system capacity is reduced with the inclusion of the square footage variable. Since the instruments are not particularly strong and the Hausman test is inclusive, I rely on the qualitative assessment of the effect of net price on kW, to lend support for using the OLS estimator instead of the 2SLS estimator.

Results and Discussion

OLS Regression Results

Below is the estimation of the pass-through rate of solar PV incentives to net price for the data presented in Table 2.6. The data include the entire sample from the five California programs, as compared to the results in Table 2.18, which are for only the subset of the data for which an instrument was available. The primary specification results (Table 2.19) show evidence of incomplete pass-through of incentives to consumers. On average, for every one dollar increase in the incentive, system price declines 54 cents. In other words, 46 cents of every dollar of consumer side incentive is captured by the supply side. A one standard deviation change in the cash incentive ($12,251 to $18,696) decreases net price by an additional $3,481 dollars. These findings are significantly different from -1 and 0 at the 5% level. Based on these estimates I reject the hypothesis that the pass-through of PV cash incentives to consumers is complete.

Considering the relatively elastic supply and demand in the PV market, this finding is not surprising. This finding is consistent with findings by Henwood (2014), Gillingham et al. (2014), Podolefsky (2013), and Wiser (2006). Results are lower than pass through found by Dong, Wiser, and Rai (2014). The variation across findings can be due to a number of factors including different model specifications, data quality, and the time period of observation.

Regarding other key price drivers, as expected, system size is a large and significant driver of net price. A change in one standard deviation of system size (1.9 kW) increases system net price by $12,272. Measures of kW squared, median household income*kW, experience*kW, and HHI*kW are insignificant.

Table 2.19

Net Price Regression Results	
	(1)
Dependent variable: Net Price (PV system total price - cash incentive)	
	OLS
After Tax Cash Incentive	-0.54***
	(0.03)
kW (system size)	6461.76***
	(489.24)
kW Squared (system size squared)	-39.99
	(47.44)
Contractor HHI-County	-0.12
	(0.33)
Median HH Income Zip (,000)	-88.06***
	(20.27)
Installer Experience (kW)	1.26*
	(0.71)
Contractor HHI-County *kW	-0.12
	(0.14)
Contractor HHI-County *kW squared	0.02
	(0.01)
Median HH Income Zip (,000) *kW	8.87
	(7.25)
Median HH Income Zip (,000) *kW squared	-0.15
	(0.70)
Installer Experience (kW) * kW	-0.41
	(0.29)
Installer Experience (kW) * kW squared	0.03
	(0.03)
Constant	28765.14***
	(9028.06)
Observations	26465
Adjusted R-squared	0.754

Includes completion year, utility, and zip code dummies.
Includes robust and zip code-clustered errors.
All dollar values in 2008 U.S. dollars.

Income Interactions

In addition to the coefficient on *INCENTIVE*, also of interest is how the pass-through rate changes under different market conditions. I hypothesize that consumers with higher income have lower incentive pass-through. Less price sensitive, higher income consumers may engage in a lower degree of price shopping. Facing more budget constraints lower income consumers may be more informed and suffer less from information asymmetries than their wealthier counterparts. Such consumers may also have a lower incentive pass-through if contractors are able to offer differentiated prices to different customer classes. It is important to note that the lowest income consumers in this case are not low income by traditional metrics such as relation to the poverty line. In the 2000 census, the weighted average U.S. income poverty levels for two person families and four person families were \$10,869 and \$17,029 respectively. In 1999, 14.2% of Californians had income below the poverty line. In this data, the average zip code level household income, \$61,500, is much higher than the poverty line or state average income. Overall the income distribution in the data is shifted to the right of the state's income distribution. This analysis addresses whether, among consumers wealthy enough to purchase solar PV, the pass-through rate is lowest for consumers with the highest income.

Hypothesis: PV consumers with the highest income have lower incentive pass-through due to asymmetric information.

To test the hypothesis regressions are run that include various specifications of income interactions (Table 2.21). Included in specifications 3 through 5 are dummies for the observations in the highest third of income and for observations in the middle third of income. Dropped from specifications 3 through 5 are the dummy for observations in the lowest third of income. Income percentiles are based on the distribution of median income (1999 California Census) for all zip codes in the pre-screened data (column 2 in Table 2.20)[27]. On average, the income distribution in the data is higher than the income distribution in the state and slightly lower than the distribution in the final regression data as shown in the table below. In the regression sample, 35% of the observations are in highest income bracket (66% and above). 32% of the data are in the lowest third income bracket.

Table 2.20

Comparison Calfiornia Median Zip Code Statistics versus Data			
	(1)	(2)	(3)
Upper Limit	**All California Zip Codes**	**Pre-Screened Data**	**Final Regression Data**
Median Income	\$42,884	\$55,869	\$56,486
Lowest Third Maximum	\$35,933	\$47,099	\$47,837
Middle Third Maximum	\$50,585	\$64,611	\$65,737
Highest Third Maximum	\$200,001	\$200,001	\$200,001

Multiple specifications are run to separately identify income's interaction with system size and incentive. Due to the high correlation between system size and incentive (.76) separating these effects at a fine level is challenging. Results are shown in Table 2.21. Specification 1 is the primary OLS specification also shown in Table 2.12. The coefficient on *MEDIAN HOUSEHOLD INCOME ZIP*KW* shows the change in net price, for every kilowatt, as income increases \$1,000. These results are not significant (t-1.22, p=.221). In Specification 2, both the interaction of income with system size and the

[27] Data included are screened for systems with missing data, installed price less than \$3/W_{DC}, installed price > \$30/W_{DC}, price net of subsidy less than zero,

interaction of income with incentive are tested. The coefficient for *MEDIAN HOUSEHOLD INCOME ZIP*KW* remains insignificant, but the coefficient for *MEDIAN HOUSEHOLD INCOME ZIP*INCENTIVE* is significant and positive, albeit small. As income increased by $10,000, holding system size constant, the pass-through rate decreases by .03 to -0.51. This finding is significant and supports the alternative hypothesis that wealthier consumers experience a lower pass-through of incentives. Specification 3 tests whether there is a difference in the interaction of income and system size for the highest income group relative to the lowest. No significant difference is found. Specification 4 however finds that the wealthiest consumers receive a lower pass-through of the incentive than the consumers in the lowest income groups. The coefficient of .11 suggests that for every dollar of incentive, the pass-through of incentive to the highest income consumers is -0.48, 11 cents less per dollar than for the lowest income group. Finally, Specification 5 strives for the greatest decomposition of income effects on system size and incentive pass-through and include dummies for both middle and high income system size and incentive interactions. The finding that highest income customers have lower incentive pass-through persists in this specification with pass-through for highest income customers 16 cents less than lower income customers.

The regression results for the income interactions are presented below in Table 2.21.

Table 2.21

Income Interactions Regression Results					
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Net Price (PV system total price - cash incentive)					
After-tax Cash Incentive	-0.54***	-0.76***	-0.54***	-0.59***	-0.61***
	(0.03)	(0.05)	(0.03)	(0.04)	(0.04)
kW (system size)	6461.76***	6879.31***	7015.29***	7022.03***	7186.78***
	(489.24)	(470.35)	(271.38)	(265.17)	(280.69)
Contractor HHI-County	-0.12	-0.11	-0.05	-0.07	-0.02
	(0.33)	(0.33)	(0.33)	(0.32)	(0.33)
Median HH Income Zip (,000)	-88.06***	-98.00***	-52.19***	-49.07***	-53.74***
	(20.27)	(20.62)	(9.44)	(9.10)	(9.55)
Installer Experience (kW)	1.26*	1.36*	1.11	1.32*	1.12
	(0.71)	(0.72)	(0.70)	(0.70)	(0.71)
kW Squared (system size squared)	-39.99	-26.51	-89.30***	-68.95***	-88.67***
	(47.44)	(47.43)	(27.99)	(26.54)	(28.08)
Contractor HHI-County *kW	-0.12	-0.10	-0.16	-0.14	-0.15
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Median HH Income Zip (,000) *kW	8.87	2.02			
	(7.25)	(6.90)			
Contractor Experience (kW) * kW	-0.41	-0.44	-0.35	-0.42	-0.34
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)
Contractor HHI-County *kW squared	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Median HH Income Zip (,000) *kW squared	-0.15	-0.35	0.60***	0.29*	0.59***
	(0.70)	(0.70)	(0.21)	(0.16)	(0.21)
Contractor Experience (kW) * kW squared	0.03	0.03	0.02	0.03	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Median HH Income Zip Code (,000) *Incentive		**0.003*****			
		(0.006)			
HH Income Zip Code Middle Third (,000)			-714.52	-1168.65	-1185.43
			(4486.64)	(4575.04)	(4586.56)
HH Income Zip Code Middle Third (,000) *kW			36.39		-43.34
			(88.14)		(128.92)
HH Income Zip Code Highest Third (,000) *kW			-1167.22	-1307.31	-1165.59
			(874.58)	(860.82)	(875.18)
HH Income Zip Code Highest Third (,000)			28.55		-376.38**
			(139.54)		(161.40)
HH Income Zip Code Middle Third (,000) *Incentive				0.04	0.03
				(0.03)	(0.04)
HH Income Zip Code Highest Third (,000) *Incentive				**0.11*****	**0.16*****
				(0.04)	**(0.04)**
Constant	28765.14***	29461.57*	27173.56*	27560.75*	27567.52***
	(9028.06)	(8764.98)	(8907.21)	(8664.89)	(8645.93)
Observations	26465	26465	26465	26465	26465
Adjusted R-squared	0.754	0.754	0.753	0.754	0.754

Includes completion year, utility, and zip code dummies.
Includes robust and zip code-clustered errors.
All dollar values in 2008 U.S. dollars.

Conclusions and Further Research

The analysis shows that incentive pass-through in the CA residential solar PV programs is incomplete. Consumer prices decline 54 cents for every additional dollar of incentive received. A large share of the incentive is captured by the solar PV contractor or other actors in the solar PV supply chain. The finding of incomplete pass-through is persistent across specifications. Also identified is a lower degree of incentive pass through for consumers in the highest income zip codes. This result could be due to such consumers engaging in a lower degree of price search behavior, placing a higher value on contractor quality, their greater reliance on personal referrals, or supplier price differentiation.

Findings of incomplete incentive pass-through have a number of policy design and evaluation implications. If the aim of incentives is to reduce costs to consumers, incomplete pass-through mutes the expected price signal and may increase the time necessary to reach capacity deployment goals. How installers utilize the rents they capture may however reduce timing delays stemming from incomplete pass-through if such monies are used to increase marketing and outreach.

A finding of incomplete pass-through is not surprising considering the relatively elastic solar PV supply and demand curves. In the long-run, solar PV markets are expected to be competitive given the presence of substitutes and surmountable barriers to entry. However, regulators should be extremely attentive to any circumstances that may result in medium to long term demand and supply inelasticities.

A scenario with very inelastic demand is unlikely. Solar PV consumers can easily substitute to grid power or other forms of self-generation such as gas engines if solar PV prices are too high. Studies to date show solar PV consumers as price responsive (Faiers and Neame, 2006). There is clear evidence of an increase in U.S. demand for solar PV as net price changed with the introduction of state and federal subsidies, and conversely a decline in Spain's PV demand after the decline in Spanish incentives.

Situations of inelastic supply are more likely, at least in the short run. Within the PV module market there have already been periods of inelastic supply. From 2004 to 2008 the supply of PV modules was constrained by the availability of purified silicon. Limited availability of high grade silicon and long-term silicon contracts, forced PV manufacturers to buy expensive silicon on the global market. High competition for silicon for computing and solar power needs resulted in unprecedented silicon prices. (Arnoldy, 2008, Gartner, 2005, Lewis, 2006). Solar PV manufacturers responded over time by reducing PV module silicon content and silicon producers also invested in silicon processing capacity, which eased the shortage in the latter part of the decade.

However, although these supply constraints existed during the data period, they do not affect the incidence of the pass-through of state level incentives because incentives are limited to, and influenced by, a smaller geographic market. CA is a price-taker for modules and in a supply constrained scenario California consumers would merely pay higher prices for the modules. As such, supply constraints that impact pass-through must be constraints faced within the local PV contractor market that affect the ability of suppliers to deliver solar PV, even in times of high demand.

Limits to labor supply may be a constraint that affects incentive pass-through. Labor supply constraints could result from barriers to entry such as licensing and certification requirements for contractors (Mass, Bing et al. 2003). Licensing and certification requirements for contractors can be useful consumer protection tools, as improper installation may create safety risks or result in poor system performance. Licensing is a mandatory requirement, while certification is usually a voluntary standard that contractors attain to differentiate them from competition and signal higher quality service. Over the last decade several incentive programs have begun to require solar PV certifications as mandatory requirements for receiving incentives. As of 2012, 12 states and Puerto Rico have specific solar contractor licensing requirements. Most states require PV installations to be done by a licensed electrical or general contractor at a minimum for installations that are not self-installed.

California incentive programs require contractors to possess one of the following licenses: A-General Engineering Contractor, B- General Building Contractor, C-10 Electrical Contractor license, or California C-46 Solar Installer license. Although an initial license is a few hundred dollars and requires experience, this requirement is unlikely to result in labor constraints since a number of firms possessed one or more of these licenses by 2008. Moreover, the C-46 license allows contractors to get the solar specialty license and install systems without having a full electrical or plumbing license. This reduces the cost of licensure for contractors who plan to only install solar systems and increases the pool of potential contractors. As of June 2009, 527 firms had received a California solar license.

In addition to license requirements, there has been a growing trend in specialized solar PV certifications, the most popular being the NABCEP certification. The North American Board of Certified Energy Practitioners (NABCEP) is a nationally-recognized, independent, voluntary certification program for PV and solar thermal system contractors. To become NABCEP-certified, contractors must have at least one year of installation experience and must document systems training and installation. Contractors must also pass a four-hour, 60-question examination, sign a code of ethics, and take continuing education courses for re-certification every three years. NABCEP's PV Installer Certification is North America's only renewable energy personnel certification that has been ANSI accredited to the internationally recognized ISO/IEC 17024 standard. NABCEP certifies contractors, not firms, although it provided its first firm level certification in September 2012. Full NABCEP certification costs $600 and tests are offered only four times a year.

Although intended as a voluntary credential, NABCEP certification is now either mandatory or is preferred for contractors who wish to participate in several state incentive programs. In Utah, NABCEP-certification is a prerequisite for qualifying for a state solar contractor license. For solar installations to be eligible for state incentive funds in Maine, Minnesota, New York, Ohio, or Wisconsin the PV systems must be installed by a NABCEP-certified professional. California, Delaware, Massachusetts, and Pennsylvania prefer or recommend that NABCEP-certified professionals install systems receiving incentives. As of November 2010, California had 231 NABCEP certified solar PV contractors. As previously noted SMUD's program offered a $200 higher incentive for NABCEP contractors.

If this trend for requiring NABCEP certification continues then short to medium term solar PV supply constraints could result. Under such a scenario, local solar PV supply can be inelastic and incentive pass-through to consumers will be zero. There is insufficient empirical evidence in the data to test this hypothesis. This hypothesis could be tested in further analysis of incentive pass-through in states that introduce mandatory NABCEP requirements. Although licensing and certification offer advantages, their introduction should be timed so as to not constrain supply and incentive impact.

This analysis focuses on the price effect of incentives to the individual consumer. Understanding this impact could be enhanced in future research projects with more detailed data on consumer income, electricity usage, and willingness to pay. To further understand the long-term impact of incentives, future analysis could assess the general equilibrium incidence in order to determine which persons ultimately benefits from the incentive. For example, solar PV contractors may use the extra rents for higher wages which can have positive macroeconomic impacts. Further analysis could also address who ultimately pays for the incentives. Such analysis would have to consider the varying electricity rates, usage, and expenditures of electricity customers.

Although measuring incidence is one of the first steps in understanding the impact of incentives on public policy goals, it does not fully explain the impact of incentives on ratepayer welfare. The actual benefits to ratepayers for incentivizing solar can vary depending on the causes for the lower pass-through.

It is often noted that incidence is about prices, and not quantities. This is indeed true from a PV consumer's perspective. PV consumers are indifferent along the various points of their demand curves regarding whether to purchase solar or use their income for other purposes. However, how rents are used by installers from incomplete pass-through can have different implications on overall ratepayer welfare since ratepayers pay for the subsidy, but may not directly benefit from it. With incomplete pass-through, installers are capturing greater rents and these rents may have positive benefits to ratepayers if directed towards activities that increase PV quantity by improving product quality or advertising to harder to reach and serve solar PV consumers. However, alternatively, installers may be dissipating rents through customer acquisition and defensive advertising focused on competing for rents from the existing solar PV customer base. This behavior would not grow the market and does not benefit ratepayers at large. A 2014 Solar Energy Industries Association (SEIA) report notes that the share of customer acquisition costs had only fallen slightly since the previous year and a strong correlation between customer acquisition cost reduction and the size of the solar company has not been observed (GTM Research and SEIA, 2014). This suggests that firms are not benefiting from economies of scale in customer acquisition. Moreover, in the presence of imperfect competition, some of the rents gained will accrue to inefficient and smaller firms and be dissipated at faster rate through such activities. The worst case scenario for ratepayers is if firms are taking all captured rents as profit. Future research examining installer firms advertising and customer acquisition expenditures and profit margins would provide useful insight into the ratepayer welfare implications from incomplete pass-through.

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Testing the Boundaries of the Solar Photovoltaic Learning System

Introduction

PV experience curves relate solar PV technology cost declines to the cumulative capacity of solar PV installed. Historically, solar PV experience curves have assumed one experience curve represents both module and non-module learning and that this learning happens at a global scale. These assumptions may be inaccurate since the learning system, and technology and geographic boundaries, are likely different between PV modules and non-module components. This paper examines how solar PV experience curves' geographic and technology assumptions affect their accuracy. This is done by testing the fit of the typical two-factor experience curve model with covariates to California, national, and global solar PV data.

The experience curve methodology is employed because it is a widely used and easy to understand model for predicting manufacturing cost declines due to improvements in production technology that result from increased installed capacity. Such curves were first used to estimate solar PV costs by Maycock in 1975 and have been used as a forecasting tool in energy models such as the Energy Information Administration's (EIA) National Energy Modeling System and the International Institute for Applied Systems Analysis' (IIASA) MESSAGE model. Experience curves are also used to justify government financial intervention in new clean technology markets (Ferioli et al., 2009; van Benthem et al., 2008; Gillingham et al. 2007; Gritsevskyi, A. and N. Nakicenovic 2000). The experience curve methodology is used here in order to situate this analysis as a follow-up to previous studies of solar PV learning that rely on experience curves to estimate PV module and non-module learning. Table 3.17 in the Appendix lists ten studies from 1997 to 2007 that rely on the experience curve methodology to estimate learning in the solar PV market.

The simplicity of inputs required to create an experience curve – a time series of technology costs, initial starting capacity, and cumulative installed capacity – have led to its regular use. However this simplicity has also led to critiques of such models' broader applicability and validity. Below, and throughout this paper, critiques of this model are acknowledged and attempts are made to correct for some of the model limitations. Interestingly, once the model deficiencies that other studies do not address are corrected, the learning relationship is no longer statistically significant.

This paper begins with an overview of the geographic and technology characteristics of the non-module component and why they warrant their own learning curve construct. Next, the experience curve model and some potential challenges with using it to estimate non-module learning are explained. Finally, study design, data, results, and conclusions are presented.

Technology boundary – the module is no longer the primary cost driver

Distributed solar PV systems' costs are historically represented as the cost of the module – the collection of photovoltaic cells that allows sunlight to be collected for conversion to electricity. However, as module costs have fallen, other non-module costs such as the inverter, wiring, hardware, labor, interconnection, permitting, and back office processing costs are increasingly representing a larger portion of total PV system costs.

The majority of PV experience curves have focused on the module cost declines. However, the share of total PV system cost represented by the module component has declined over time, especially in smaller PV systems. In 2008, the module cost represented approximately 45% of the installed cost of residential PV systems. By 2014, modules represented only approximately 25% of residential solar PV installed costs (Barbose and Dargouth 2015). This trend towards proportionally higher non-module (balance of system) costs leads one to question whether the historical experience curve model is still appropriate for representing PV cost declines.

Geographic boundary of installed capacity- when location matters

The key variable of interest in an experience curve model is the market cumulative capacity. The market is defined as the installed capacity or production that can affect individual system costs. Actors within this market trade and share common learning and experience._The market for modules is global, but the market for the module components of the system may not be. By extrapolating global module learning to the entire learning system, modelers assume that the non-module system components are similarly affected by global PV installed capacity. However, as noted earlier, non-module costs include activities such as labor and permitting that are more local. Burkhardt et al. (2015) detail well how variations in local regulations can lead to significant differences in solar PV non-module costs. Schaeffer et al. (2004) and Shum and Watanabe (2008) posit that the non-module learning system is more local than the module learning system due to cross, and potentially within, country differences in PV system designs, regulations, financial incentives, and electric codes. Similarly, in an examination of non-module prices in US states I expect to find that cumulative experience is associated with lower costs more at the state, or sub-state level than national or global.

In addition to assuming a global learning system, the traditional experience models assume no knowledge spillovers and that the impact of experience does not decay with distance. For example, the traditional model assumes that the installations of a PV system in Germany, and a PV installation in Nevada, affect PV system costs in California similarly and that this effect is the same for module and non-module costs.

For non-module costs I hypothesize that spillovers across states will be positive, but limited since not all knowledge is appropriable, i.e. a state or firm is not able retain within its borders all of the learning occurring in its local, sub-national market.

There are a number of pathways by which learning in one state can influence another. Information sharing can occur through labor migration, best practices sharing across regulatory and government bodies, and networks and conferences for knowledge dissemination. Spillovers are likely a function of geographical distance, market size, political boundaries, and the extent of solar PV project customization.

Various industry studies have shown that the impact of experience may dissipate over longer distance since distance limits the opportunities for learning-by-doing and information sharing (Keller 2002; Jaffe, Trajtenberg, and Henderson 1993). There is also evidence that technology transfers more easily between countries that are geographically closer (Keller 2002; Davidson and McFetridge 1985). However, distance decay can be mitigated, to a degree, by the increased opportunities for information exchange facilitated by advances in communication (Feldman 1999).

For solar PV systems, knowledge transfer may also have discontinuous jumps at political boundaries, especially since non-module activities are regulated by distinct political jurisdictions. Burkhardt et al. (2015) identify more than 18,000 US local authorities that have jurisdiction over some aspect of non-module costs. Tong (2012) explains that some installers avoid certain jurisdictions altogether due to the complications of dealing with local requirements.

Schaeffer et al. (2004) offer anecdotal evidence of spillovers across European countries' non-module prices. They find that although in Europe non-module costs are mostly national, there is some international spillover. Comparing four countries' 2002 non-module prices, they find that although non-module prices were higher in the countries newer to the PV market, the prices for new entrants were still lower than the price for older programs at their onset.

Implications of misspecification of technology and geographic boundaries

Misspecification of the technology and geographic boundaries can lead to modeling and forward costs forecast errors, in particular if module and non-module costs are declining at different rates and their relative share of costs is changing over time. Barbose and Dargouth (2015) find that from 1998 to 2014, module prices fell by $4.4/W (85%) while implied non-module costs fell only by $3.7/W (52%). Schaeffer et al. (2004) find that using national, German PV capacity, which was growing faster than global capacity, to predict German module costs underestimates learning because the correct market definition, global, was growing at a slower pace than development within the country. Various researchers (Duke, Williams, and Payne, 2005; Duke, 2002; Wene 2000) comment on the potential issues with misspecification if solar PV modules and non-module components are not the same learning system. However they do not pursue analysis to further substantiate their conclusions.

Overestimation of the experience rate will underestimate the time needed for solar PV costs to reach parity with fossil generation in a given market. Too low an estimate will underestimate the role of incentives, and cumulative deployment as cost drivers. Both outcomes will have implications for energy policy and renewable incentive program design, technology preferences, and technology roadmaps. This issue is not unique to solar PV, and has implications for all clean energy technology development. For example, in the field of energy efficiency, Desroches et al. (2013) find that incorporating learning rates into energy conservation models increases the national consumer net present value of potential standard levels and in some cases the inclusion of a positive experience rate is the deciding factor in an energy efficiency standard being cost-effective.

Revisiting experience curves for solar PV

Given the differences between module and non-module costs and markets, there is a growing perspective that solar PV systems are composed of at least two distinct learning systems, the module learning system, and the non-module system (Shum and Watanabe 2008; Schaeffer 2004; IEA 2000). These systems include different actors, value chains, and potentially a geographically different scope of experience.

Although this different framing for solar PV has been acknowledged before, empirical evidence has been limited. Harmon (2000) notes the difficulties with estimating the non-module cost curve including, obtaining non-module costs, the customized nature of PV systems, and the fact that non-module costs measured in dollars per watt can be subject to scaling factors.

Schaeffer et al. (2004) and Shum and Watanabe (2008) present empirical evidence of learning in the PV non-module system using national, instead of global, definitions of the geographic boundary. Schaeffer estimates non-module experience curves for Germany and the Netherlands (1992 to 2001) using national cumulative capacity and non-module prices. He finds similar estimates for non-module and module learning. Similarly, Shum and Watanabe (2008) estimate a non-module learning rate for the U.S. market using 1994 to 2003 national grid connected distributed capacity as the experience variable. Bollinger and Gillingham (2014) use a model of installer firm pricing behavior to quantify appropriable and non-appropriable learning-by-doing in the California solar PV market between 2002 to 2012. They find that learning by installers within a county can reduce non-module costs by $0.36/W with the addition of 100 installations. They also find that 1,000 installations by competitors outside of the county reduced installer non-module costs by $0.005/W, suggesting learning spillovers from competing installer firms. They do not identify the effect of experience from non-direct competitors or comment on cross-state learning or learning distance decay.

These studies provide some analysis of alternatives to a global boundary for non-module systems; however they stop short of comparing and testing boundaries smaller than national. As such they are unable to offer evidence of the national boundary as superior to a global, or an alternative, market definition. This paper aims to further analyze whether a smaller market definition, specifically state, better predicts solar PV non-module prices.

In doing this analysis I would be remiss if I did not address the potential weaknesses with the experience curve model. Although not addressed in the majority of existing studies, these issues may limit the effectiveness of this tool for forecasting future non-module price declines.

First, omitted variable bias may result from experience curves' reliance on cumulative production as the only explanatory variable for cost declines. If there are other explanatory variables excluded from the model, whose coefficients are non-zero, then the coefficient on cumulative production will over or underestimate its effect. This issue is more attenuated the more correlated with cumulative capacity these omitted variables are. For example, exclusion of a time trend, which can be a general, albeit imprecise, measure of technological progress, may result in cumulative production erroneously appearing as a more significant factor. Papineau (2006) finds that adding a time trend to a PV module experience curve renders cumulative capacity insignificant. Other omitted variables may include R&D expenditures and neighboring markets' installed PV capacity, which may be relevant if there is knowledge spillover across geographic markets.

Omitted variable bias may also result from the conflation of technology learning and scale effects. Technology learning, such as learning-by-doing, arises from aggregate increases in cumulative production and the development of new production functions. Scale effects, such as economies of scale, result from increased quantity in a given period and a more efficient use of inputs. As Papineau (2006) notes regarding the originators of the experience curve's approach, "The experience curve was the result of labour learning, managerial learning, process improvement, product standardization, and economies of scale, though they never decompose these effects to analyze their individual roles." Only in the case of constant returns to scale will there be no omitted variable bias from not including a scale effect term. Some researchers, such as Solderholm and Sundqvist (2007), have separately identified scale effect by including a current rate of output in the model. In this paper, omitted variable bias concerns will be addressed by including in certain specifications a time trend, current installed capacity, and a variable to represent neighboring markets' cumulative capacity.

Accurate use of the experience model also requires a certain degree of data quality that may be less widely available for solar PV systems. First, the experience curve models the effects of cumulative deployment on costs, however most studies use price as a proxy for costs since cost data are rarely available. For example, for the ten studies discussed in Table 3.17, all but one use price as a proxy for module and non-module PV costs. Prices may show a different trend than costs, especially if considering a relatively short time period and if price-cost margins are not constant in the data time series. Prices may change for reasons unrelated to production efficiencies and input prices, which also cause costs to change. For example, as I note in Paper 2, if there is any pass through of government incentives, prices may change due to fluctuating incentive levels. Inclusion of subsidy measures may control for such concerns.

The general use of cost or price data as a dependent variable may also result in an endogeneity concern. The experience curve model assumes that cumulative capacity is an exogenous variable. However, cumulative experience may be simultaneously determined with price, e.g. more PV capacity built because of the price, and the price is determined by the amount of capacity. In this case the cumulative capacity term and the error term may be correlated. If this is so, OLS estimation of the experience curve equation will be biased and inconsistent. Typical experience curves do not attempt to control for this endogeneity. Due to the small number of observations, I am not able to control for this endogeneity here.

In the previous chapter, "Pass through of solar incentive to consumers: The early years of California's recent wave of solar PV incentives," I address a related endogeneity between prices and the capacity installed at each location during this time period. As I note, this type of endogeneity, consumers increasing the system size to benefit from lower unit costs, is not expected to be pronounced during this time period for the following reasons. First, under the incentive programs, PV consumers had restrictions on the extent to which they can use or profit from excess generation. Net metering allows residential consumers to bank excess generation against their future utility electricity purchases, but only through the calendar year. Program rules also required that systems not be sized greater than onsite load and that applicants submit proof of twelve months of historical electricity usage. Finally, all of the programs had a cap on system size, and a smaller cap on system size eligible for incentives. These temporal and program conditions reduce the economic incentive for larger sized systems. Gillingham et al. (2014) decline to address this potential endogeneity in their analysis based on their understanding that system sizing decisions are nearly always based on electricity consumption and roof size. However, I anticipate that going forward, as policies, such as feed-in-tariffs, that allow residential consumers to export more power are adopted and as customer-sited battery storage increases in popularity, the economic rationale to oversize systems will increase.

Another data challenge that arises when looking at non-module costs specifically is that these data are less available and reliable. For example, although the California incentive programs collected module and non-module cost data in these early years of the programs (1998-2008) the data provided were of varying, and at times poor, quality. As such, the few studies that have done non-module price experience curves during this time period, (Shum and Watanabe (2007), Schaeffer et al. (2004), estimate non-module prices as the total PV system price adjusted to exclude module costs, based on a module price index. This use of module price indexes is justified given the standardization of modules and prices; however there is variation in module acquisition price as a function of volume of business which is not captured by module indexes. Smaller installers and smaller systems likely have higher module costs. As such this factor contributes to measurement error in PV non-module experience curves.

Finally another source of varying learning rates may be different datasets, such as data covering different time periods or different definitions of cumulative capacity. For example, Soderholm and Sundqvist (2007) in their study of learning rates in European wind power markets found that changing the time period of their dataset and choice of variable of interest had significant effects on their learning curve estimates. I test for the effect of such factors by doing sensitivities to data start and end dates and to different definitions of installed capacity.

Paper Overview

This paper tests how the choice of geographic and technology assumptions affect estimates of solar PV experience curves. Experience rates are generated using reduced form regression analysis. Empirical tests for non-nested models are used to compare the state, national, and global models. A similar analysis is conducted using multiple state observations as a means to have a larger sample size. I hypothesize that a more local definition of the market will be a better fit with observed cost declines. Also analyzed are the potential impacts of installed PV capacity in neighboring states on an origin state's non-module prices. Given the possible issues with the experience curve model noted above, issues, such as omitted variable bias, are corrected by including time trends, other covariates, and fixed effects in the models. Although an advancement over current practice, it is worth noting that inclusion of a time trend is a very imprecise way to control for exogenous technological change. It assumes that technological change is monotonic, which is unlikely to be the case for something such as improvements in internet based, remote solar PV site assessments. Such technological change tends to occur in more fits and starts and might be better represented by a higher order functional form. Similarly, the inclusion of a linear term for economies of scale is also likely mispecified since economies of scale are generally considered more convex than linear. However, the small size of this data set does lend itself to experimentation with higher order specifications of these terms. Interestingly, most other experience curve studies fail to include any terms to represent technological change and economies of scale. This suggests that there is a need for future studies to be more cognizant of the conflation of these three factors – learning, exogenous technological change, and economies of scale – and to explore various combinations of functional forms to better approximate real world conditions.

In this analysis, the significance of results is robust to some of these corrections but not to all. For example once state fixed effects are introduced in the multi-state analysis the finding of learning and state spillovers are highly insignificant. However, the different model specifications employed provide some useful insight into the limitations of experience curves and the caution that should be applied with using experience curve model results to justify subsidies or government intervention.

Study Design

The model specified below is used to estimate solar PV module and non-module cost declines as experience, represented by cumulative installed PV capacity, increases.

$$\frac{C(Q_t)}{C(Q_o)} = (\frac{Q_t}{Q_0})^{-b} \qquad (1)$$

Where experience (Q) is watts of cumulative installed PV systems and Cost (C) is average module or non-module price per Watt since actual cost data are not available.[28] Of interest is the learning coefficient, *b*, which represents the elasticity of cost to cumulative capacity and is also a function of initial starting conditions ($C(Q_o)$ and Q_o). Typically experience curve models include $C(Q_o)$ as a right hand side variable. However, it is included here as part of the dependent variable to make clear that of interest is the ratio of current costs to initial costs. This becomes more important in the multi-state analysis when states have different initial starting costs. Taking the log of both sides of (1) allows estimation of *b* using Ordinary Least Squares and equation (1) can be represented by a straight line with slope $-b_1$ as in equation (2). As is often the case in experience curves, cumulative capacity Q is lagged one year to account for the time delay in learning. If learning exists, the experience coefficient b_1 will be negative and significant. The Progress Ratio (PR), the usually cited value for learning, equals 2^{-b}. The PR represents what the cost will be after a doubling of cumulative capacity. For example a PR of .95 means that costs are 95% of what they were before capacity doubled. The complement to the PR is the Experience Rate which equals $1-2^{-b}$ and is expressed as a constant percentage cost decline as experience doubles. The term ε_t is an additive disturbance term which is assumed to have a zero mean, constant variance, and to be independent and normally distributed. The model's reliance on a double logarithmic representation of learning, where distance along the axes is directly proportional to the percentage change in cumulative sales and price, makes it easier to see and compare performance improvements. The log-log functional form has been historically utilized for experience curves because of its high goodness of fit and simplicity relative to other functional forms (van Sark, 2008; Grübler et al., 1999).

$$\log\frac{C(Q_t)}{C(Q_o)} = \alpha + b_1 \log(\frac{Q_{t-1}}{Q_{0-1}}) + \varepsilon_t \qquad (2)$$

[28] It is common practice to use price a proxy for costs in experience curve models. See Table 3.17 for examples.

In order to separate scale effects from learning effects I also employ the following model specification that includes a term for capacity installed within a given period, q_t, in this case watts of solar PV added in a given year *t*.

$$\log\frac{C(q_t,Q_t)}{C(Q_o)} = \alpha + b_1 \log(\frac{Q_{t-1}}{Q_{0-1}}) + b_2 \log(q_t) + \varepsilon_t \qquad (3)$$

California Experience Curve Model

Equations (2) and (3) are used to estimate what geographic definition of experience is a better predictor of costs in the California non-module market and the global module market respectively. OLS is used to estimate non-module and module prices using global, national, and state cumulative capacity respectively for a total of 20 model runs. For each technology set (module and non-module) four different specifications are run for the state capacity definition and three for US and global capacity. Also included are different additional regressors such as installed year, current year capacity (to represent economies of scale) and average system size to address potential omitted variable bias. Average size is only available for the state capacity data so it is not included in the national and global models. As noted in the results and discussion section, the findings and the ability to address omitted variable bias are constrained by the limited data size (11 observations).

There are a few empirical tests available to compare which of these models is superior at predicting module and non-module prices. Let us use as an example two models for non-module prices where Model 0 has state level capacity as the main regressor and Model 1 has US (national capacity) as the main regressor. The *encompassing model* popularized by Mizon and Richard (1986) tests whether the features of Model 1 are explained by Model 0. The test is conducted by artificially nesting the two models and estimating coefficients for the regressors unique to Model 1, regressors unique to Model 0, and regressors common to both models. If the coefficient on state capacity is zero, and the coefficient on U.S. capacity is non-zero, this would imply that the model with US capacity is superior.

Greene (2003) highlights two issues with this approach. First, the coefficient on the shared regressors in the model is still a mixture of the two models. Second, and most concerning for the models in this analysis, is that results may have high standard errors due to high levels of collinearity between the variables in the respective models. In addition to being on similar trajectories, a high collinearity also exists between the capacity variables because California, the state under examination, represents the lion's share of US solar PV capacity in the time period (67%). When the model is run to include all three capacities (state, US, and global) the results are insignificant and non-sensical, with unrealistically high learning rate for state capacity and a positive coefficient on national capacity. As such I conclude that the variables are too collinear to use the encompassing test.

Table 3.1

Single State Analysis Capacity Correlations				
	State Cumulative Capacity (Watts, 1-Year Lag) , log	U.S. Cumulative Capacity (Watts, 1-Year Lag) , log	Global Cumulative Capacity (Watts, 1-Year Lag), log	Cumulative State System Installs (1-Year Lag), log
State Cumulative Capacity (Watts, 1-Year Lag) , log	1			
U.S. Cumulative Capacity (Watts, 1-Year Lag) , log	0.999	1		
Global Cumulative Capacity (Watts, 1-Year Lag), log	0.9853	0.9901	1	
Cumulative State System Installs (1-Year Lag), log	0.9906	0.9905	0.9913	1

The *comprehensive approach,* detailed in Greene (2003), presents alternative models for comparing non-nested, linear models that rely on the density function as the characterization of the data generating process. Let $f_0(y_i|\text{ data, }\beta_0)$ be the assumed density under Model 0 and define the alternative model, Model 1, likewise as $f_1(y_i|\text{ data, }\beta_1)$. Then a comprehensive model that subsumes both of these is:

$$f_c(y_i|\text{ data, }\beta_0, \beta_1) = \frac{[f_0(y_i|\text{ data, }\beta_0)]^{1-\lambda}\,[f_1(y_i|\text{ data, }\beta_1)]^{\lambda}}{\int_{range\_of\_yi}[f_0(y_i|\text{ data, }\beta_0)]^{1-\lambda}\,[f_1(y_i|\text{ data, }\beta_1)]^{\lambda}\,dy_i}$$

Once the comprehensive model is estimated, a test of $\lambda = 0$ or $\lambda = 1$ is used to assess the validity of Model 0 or Model 1 respectively. I will use two versions of the comprehensive approach, the J-test and the Cox-Pesaran test, to determine whether Model 0 can be rejected in favor of Model 1, whether Model 1 can be rejected in favor of Model 0, whether both should be rejected, or whether neither should be rejected. If the p-value of each hypothesis test is significant then the model under estimation can be rejected for the other model. These tests do not require nesting the two models in a manner subject to collinearity concerns. My hypothesis is that global capacity will be the best predictor of module prices, while state (more local) capacity will be a better predictor of non-module prices.

Multi- state experience curve model

A multi-state model is used to test whether state-level experience is a significant driver of PV non-module costs by regressing non-module cost on state capacity using an unbalanced pooled panel data set of state level observations. I focus on non-module costs since there is variation in average non-module costs across states. A version of the previously specified experience curve models (2) and (3) is used for the multi-state analysis. The regression is run using 2004 through 2008 annual cost and capacity observations for 13 states.

In order to control for time-varying and state-specific factors that might influence non-module costs, time and state fixed effects are included (Model 4). Also tested is a model including specific state-varying factors such as incentives, supplier wages, electricity price, and current capacity instead of state fixed effects (Model 5). Model 5 is included because given the small sample size it makes sense to also estimate learning with this more parsimonious specification.

Model 4:

$$\log\left(\frac{Cnm_{i,t}}{Cnm_{i,t_o}}\right) = \alpha + b_{\backslash 1}\log\left(\frac{Q_{i,t-1}}{Q_{i,t_o-1}}\right) + b_2 \log EOS_{i,t} + \theta_t + \tau_i$$

Where for a given state and year, experience (Q) is watts of cumulative installed PV system, Cost ($\frac{Cnm_{i,t}}{Cnm_{i,t_o}}$) is average non-module price per Watt / average non-module price per Watt at initial quantity, *EOS* is current year capacity installed (watts) as a proxy for economies of scale, (θ) is time fixed effects, (τ) is state fixed effects, and where the coefficient, b_1, on $\log\left(\frac{Q_{i,t-1}}{Q_{i,t_o-1}}\right)$ is the percent change in non-module price due to change in cumulative capacity for U.S. non-module learning systems.

Model 5:

$$\log\left(\frac{Cnm_{i,t}}{Cnm_{i,t_o}}\right) = \alpha + b_1\log\left(\frac{Q_{i,t-1}}{Q_{i,t_o-1}}\right) + b_2 \log I_{i,t} + b_3 \log W_{i,t} + b_4 \log E_{i,t} + b_5 \log S_{i,t} + b_6 \log EOS_i + \theta_t$$

Where for a given state and year, experience (Q) is watts of cumulative PV systems installed, Cost (Cnm) is average non-module price per Watt, *I* is state and federal incentives, *W* is average electrician wages, *E* is average electricity rates, *S* is average system size, *EOS* is current year capacity installed (watts) as a proxy for economies of scale, (θ) is time fixed effects , and where the coefficient, b_1, on $\log\left(\frac{Q_{i,t-1}}{Q_{i,t_o-1}}\right)$ is the percent change in non-module price due to change in cumulative capacity for U.S. non-module learning systems.

I hypothesize that in both models b_1 will be significant and negative suggesting that state capacity is a significant driver of non-module costs.

Data Overview

Dependent variable: cost

PV installed cost, location, customer type, incentives, and equipment data are from Lawrence Berkeley National Laboratory's 2009 Tracking the Sun II report.[1] The data include more than 52,000 U.S. PV systems in 15 states installed 1998 through 2008. A subset of the data, 43,787 systems, representing 189 MW, is used to create the cost data for this analysis. For the California analysis the data include 36,020 systems totaling 151.3 MW.

The dependent variable, *Cnm*, is the mean average state annual PV project-level non-module installed cost. Non-module cost is calculated as installed cost minus module cost. Except for the exclusion of PV system sales tax, the total installed cost reflects the final pre-rebate price. This price paid is reported to solar PV incentive program administrators. Installed cost is measured in dollars-per-peak-watt ($/Wp) and is used as a proxy for system cost. Peak-watt is defined as the module's power output under ideal conditions.

Since limited project level PV system module cost data are available, module cost used is the global average annual module price from Navigant Consulting's Global Power Module Price Index. The index price is the average of the global retail sales prices for "Power Modules" which are defined as including modules larger than 75 watts, and buyers who purchase modules in smaller quantities (Navigant Consulting, 2009). All cost and incentive data are adjusted to real 2008 dollars using the monthly Consumer Price Index.

Experience variables

State and US cumulative capacity data are from Sherwood, L. 2009. *U.S. Solar Market Trends 2008*. Global cumulative installed capacity is from the International Energy Agency PVPS reports. The experience variable is restricted to decentralized, on-grid installations. Installations include all on-grid (residential and non-residential systems of all sizes). The model is also tested using cumulative installs (number of systems) lagged, instead of cumulative capacity.

During the analysis period, 1998 through 2008, California represented the majority (67%) of US PV capacity. During this analysis period, California's average solar PV non-module price declined 34%, and the state underwent slightly over six doublings in cumulative state capacity. US capacity and global capacity also doubled approximately six times during the period. The data in the multi-state analysis include Arizona, California, Connecticut, Massachusetts, Maryland, Minnesota, New Jersey, Nevada, New York, Oregon, Pennsylvania, Vermont, and Wisconsin.

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[29] See Wiser et al. (2009), for full trends report.

Controls: other average state-year variables

The data also include information on system installation year, average system size, and average after-tax incentives that is used in the estimations. State-year mean hourly electrician's wages and mean annual retail electricity rates are from the Department of Labor's Occupational Employment Statistics (OES) Survey and US Energy Information Administration respectively.

Data screening

The analysis is restricted to states for which cost data and the installs are known. The dependent variable is the average installed cost in a given state and year, and so excluded from the data are any state-year observations with fewer than twenty underlying system observations (21 state year observations composed of 161 PV system observations are excluded). Also excluded are the 2008 NJ SREC program systems due to lack of incentive data.

To avoid excessive influence of outliers, to eliminate data errors, and to provide a more homogenous technology set, the following types of systems are removed to create state-year average data: systems with missing data, installed price less than $3/W_{DC\text{-}STC}$, installed price > $30/_{DC\text{-}STC}$, systems greater than 10 kW, price net of subsidy less than zero, battery-operated systems, thin-film or hybrid technologies, and Building Integrated Photovoltaics. The data include residential, commercial, government and non profit systems, but for observations with consumer segment not known, it is assumed that systems less than or equal to 10kW are residential, i.e. all the data in the final data set. Due to lack of data, inverter costs are not excluded from non-module costs; however inverter prices should not be different across states since inverters are part of a national market.

Tables 3.2 through 3.5, and graphs 3.1 and 3.2, present data, regression variables, and plots of dependent variables and variable of interests for the California and the multi-state models.

Table 3.2

Data for California Analysis

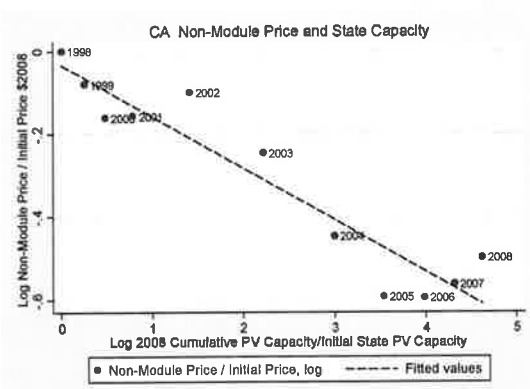
Year	Non-Module Price $/W	Initial Non-Module Price $/W	Module Price $/W	Initial Module Price $/W	State Cumulative Capacity (Watts, 1-Year Lag)	U.S. Cumulative Capacity (Watts, 1-Year Lag)	Global Cumulative Capacity (Watts, 1-Year Lag)	State Capacity Installed in Current Year (watts)	US Capacity Installed in Current Year (watts)	Global Capacity Installed in Current Year (watts)	Mean System Size (Watts)
1998	$6.80	$6.80	$4.94	$4.94	3,386,825	6,300,705	95,230,000	956,696	1,852,519	51,766,000	2,694
1999	$6.28	$6.80	$4.87	$4.94	4,343,521	8,153,224	147,000,000	1,135,510	2,825,234	91,249,000	2,496
2000	$5.79	$6.80	$4.74	$4.94	5,479,035	10,978,459	238,250,000	1,953,860	3,899,165	162,987,000	2,707
2001	$5.81	$6.80	$4.25	$4.94	7,432,896	14,877,624	401,240,000	6,469,930	10,433,477	223,581,000	3,167
2002	$6.15	$6.80	$3.89	$4.94	13,902,827	25,311,100	624,820,000	17,126,120	22,726,551	296,243,000	3,409
2003	$5.32	$6.80	$3.63	$4.94	31,028,949	48,037,651	921,060,000	36,742,220	45,394,961	426,209,000	4,002
2004	$4.35	$6.80	$3.82	$4.94	67,771,171	93,432,612	1,347,270,000	48,736,990	57,575,198	716,931,000	4,103
2005	$3.77	$6.80	$4.02	$4.94	116,508,161	151,007,810	2,064,200,000	65,763,280	79,168,361	958,216,000	4,180
2006	$3.76	$6.80	$4.16	$4.94	182,271,441	230,176,171	3,022,420,000	71,243,280	104,638,278	1,750,851,000	4,361
2007	$3.88	$6.80	$4.13	$4.94	253,514,722	334,814,449	4,773,270,000	91,815,760	152,142,063	1,246,565,000	4,471
2008	$4.14	$6.80	$3.65	$4.94	345,330,483	486,956,512	6,019,840,000	178,696,520	277,185,321	2,200,364,000	4,418

*All data average value for state year except for cumulative capacity and current year capacity variables.

Table 3.3

Regression Variables Summary for California Analysis (11 observations)				
Variable	Mean	Std. Dev.	Min	Max
Non-Module Price/Initial Non Module Price	0.7	0.2	0.6	1.0
Module Price/Initial Module Price	0.8	0.1	0.7	1.0
State Cumulative Capacity (Watts, 1-Year Lag) / Initial State Cumulative Capacity (Watts, 1-Year Lag)	27.7	34.9	1.0	102.0
U.S. Cumulative Capacity (Watts, 1-Year Lag) / Initial U.S. Cumulative Capacity (Watts, 1-Year Lag)	20.3	25.3	1.0	76.8
Global Cumulative Capacity (Watts, 1-Year Lag) / Initial Global Cumulative Capacity (Watts, 1-Year Lag)	18.8	21.2	1.0	63.2
Cumulative State System Installs (1-Year Lag) / Initial Cumulative State System Installs (1-Year Lag)	39.0	41.6	1.0	123.6
State capacity watts installed in current year	47,300,000	54,000,000	956,696	179,000,000
U.S. capacity watts installed in current year	68,900,000	84,300,000	1,852,520	277,000,000
Global capacity watts installed in current year	739,000,000	724,000,000	51,800,000	2,200,000,000
Installation Year	2003	3.3	1998	2008
Mean System Size (Watts)	3.6	0.8	2.5	4.5

Graph 3.1



** Plots for California non-module price versus global and national cumulative capacity are similar.*

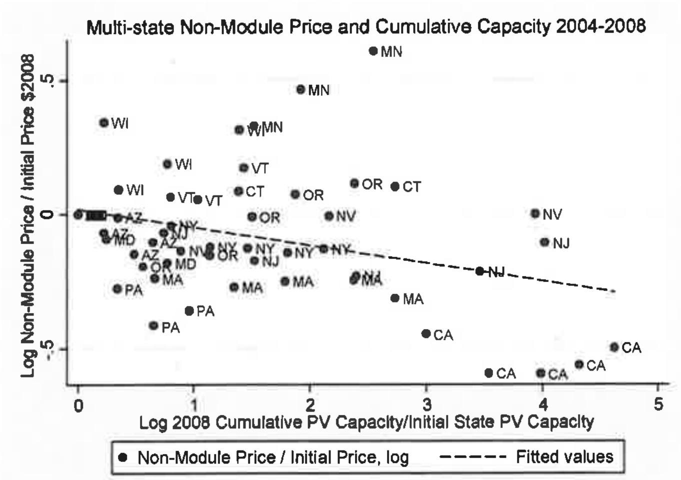
Table 3.4

Data for Multi-State Analysis											
state	year	Non-Module Price $/W	Initial Non-Module Price $/W	Non-Module Price/ Initial Non-Module Price $/W	Cum. Capacity (Watts, 1-Year Lag)	Initial Cum. Capacity (Watts, 1-Year Lag)	State Capacity Installed in Current Year	Mean System Size (Watts)	Mean Incentive	Mean Hourly Electrician's Wage	Mean Retail Electricity Price $/kWh
AZ	2004	$4.01	$4.01	1.00	9,874,670	9,874,670	2,341,000	3,435	$4.19	$20.39	$0.096
AZ	2005	$3.74	$4.01	0.93	12,300,000	9,874,670	1,559,000	3,280	$4.03	$19.29	$0.098
AZ	2006	$3.97	$4.01	0.99	13,900,000	9,874,670	2,148,000	4,212	$4.39	$19.30	$0.100
AZ	2007	$3.46	$4.01	0.86	16,100,000	9,874,670	2,802,000	4,793	$3.93	$19.88	$0.100
AZ	2008	$3.61	$4.01	0.90	18,900,000	9,874,670	6,429,000	5,218	$3.62	$20.36	$0.103
CA	2004	$4.35	$6.80	0.64	67,800,000	3,386,825	48,736,990	4,103	$3.75	$27.21	$0.139
CA	2005	$3.77	$6.80	0.55	117,000,000	3,386,825	65,763,280	4,180	$3.15	$26.37	$0.138
CA	2006	$3.76	$6.80	0.55	182,000,000	3,386,825	71,243,280	4,361	$3.22	$26.84	$0.153
CA	2007	$3.88	$6.80	0.57	254,000,000	3,386,825	91,815,760	4,471	$2.89	$26.57	$0.150
CA	2008	$4.14	$6.80	0.61	345,000,000	3,386,825	178,696,520	4,418	$2.55	$26.65	$0.138
CT	2006	$4.45	$4.45	1.00	224,950	224,950	672,000	4,582	$5.17	$26.36	$0.180
CT	2007	$4.85	$4.45	1.09	901,710	224,950	2,525,000	5,059	$4.93	$26.06	$0.198
CT	2008	$4.94	$4.45	1.11	3,442,660	224,950	5,283,000	5,521	$4.74	$25.70	$0.196
MA	2004	$5.38	$6.83	0.79	586,800	303,000	583,000	2,732	$5.37	$29.27	$0.134
MA	2005	$5.21	$6.83	0.76	1,169,800	303,000	640,000	3,080	$5.39	$27.87	$0.148
MA	2006	$5.32	$6.83	0.78	1,810,272	303,000	1,452,000	3,110	$5.28	$27.95	$0.177
MA	2007	$5.35	$6.83	0.78	3,262,072	303,000	1,381,000	3,306	$5.19	$27.37	$0.168
MA	2008	$4.99	$6.83	0.73	4,643,072	303,000	2,884,000	3,856	$4.69	$27.59	$0.177
MD	2006	$6.48	$6.48	1.00	372,790	372,790	99,000	2,548	$2.56	$24.15	$0.104
MD	2007	$5.91	$6.48	0.91	475,310	372,790	321,000	2,614	$2.51	$23.89	$0.123
MD	2008	$5.40	$6.48	0.83	807,720	372,790	2,242,000	3,392	$2.60	$24.06	$0.138
MN	2004	$3.14	$3.14	1.00	51,940	51,940	105,000	2,547	$2.30	$30.25	$0.090
MN	2006	$4.37	$3.14	1.39	237,670	51,940	69,000	3,197	$3.06	$28.33	$0.093
MN	2007	$5.01	$3.14	1.59	355,430	51,940	110,000	3,786	$2.96	$27.67	$0.095
MN	2008	$5.78	$3.14	1.84	659,360	51,940	284,000	2,644	$3.24	$27.14	$0.097
NJ	2004	$5.26	$5.64	0.93	1,800,000	858,000	2,136,000	5,749	$6.28	$32.46	$0.128
NJ	2005	$4.74	$5.64	0.84	3,936,000	858,000	5,520,000	6,428	$6.02	$31.28	$0.129
NJ	2006	$4.48	$5.64	0.79	9,456,000	858,000	17,878,000	6,712	$6.01	$30.91	$0.137
NJ	2007	$4.54	$5.64	0.81	27,300,000	858,000	20,448,000	7,124	$5.50	$31.18	$0.147
NJ	2008	$5.06	$5.64	0.90	47,800,000	858,000	22,454,000	7,014	$4.78	$30.11	$0.157
NV	2005	$5.31	$5.31	1.00	375,871	375,871	117,000	3,297	$5.03	$25.31	$0.112
NV	2006	$4.46	$5.31	0.84	917,150	375,871	539,000	4,117	$4.24	$25.02	$0.118
NV	2007	$5.17	$5.31	0.97	3,261,616	375,871	2,336,000	4,061	$3.72	$27.40	$0.123
NV	2008	$5.16	$5.31	0.97	19,200,000	375,871	15,917,000	4,244	$3.29	$26.96	$0.119
NY	2004	$5.46	$5.69	0.96	3,926,380	1,753,720	1,529,770	3,786	$5.43	$30.42	$0.166
NY	2005	$5.04	$5.69	0.89	5,510,460	1,753,720	2,021,960	4,581	$5.20	$30.47	$0.173
NY	2006	$5.01	$5.69	0.88	7,604,190	1,753,720	2,967,650	4,614	$5.61	$30.80	$0.160
NY	2007	$4.94	$5.69	0.87	10,700,000	1,753,720	3,793,900	5,133	$5.44	$31.23	$0.177
NY	2008	$5.00	$5.69	0.88	14,600,000	1,753,720	7,027,000	4,876	$5.31	$32.04	$0.183
OR	2004	$3.63	$4.41	0.82	456,200	260,000	358,000	2,944	$4.35	$29.17	$0.082
OR	2005	$3.79	$4.41	0.86	813,700	260,000	353,000	3,290	$3.95	$28.62	$0.080
OR	2006	$4.37	$4.41	0.99	1,167,000	260,000	529,000	3,183	$4.55	$28.57	$0.080
OR	2007	$4.74	$4.41	1.08	1,695,600	260,000	1,123,000	3,103	$4.78	$28.61	$0.085
OR	2008	$4.94	$4.41	1.12	2,818,800	260,000	4,832,000	3,461	$4.82	$28.62	$0.085
PA	2004	$6.68	$6.68	1.00	318,800	318,800	128,000	3,323	$5.20	$25.82	$0.109
PA	2005	$5.07	$6.68	0.76	446,600	318,800	167,000	4,394	$5.56	$26.77	$0.109
PA	2006	$4.42	$6.68	0.66	613,500	318,800	221,000	3,666	$6.12	$26.91	$0.111
PA	2007	$4.68	$6.68	0.70	834,500	318,800	103,000	4,455	$5.69	$27.09	$0.114
VT	2004	$4.84	$4.84	1.00	170,700	170,700	166,000	2,765	$2.76	$19.29	$0.147
VT	2006	$5.17	$4.84	1.07	380,800	170,700	44,000	3,010	$2.98	$19.89	$0.143
VT	2007	$5.11	$4.84	1.06	480,600	170,700	100,000	2,784	$2.79	$19.50	$0.147
VT	2008	$5.75	$4.84	1.19	716,500	170,700	236,000	3,235	$2.55	$19.70	$0.145
WI	2004	$3.94	$3.94	1.00	344,000	344,000	85,000	2,260	$2.33	$24.61	$0.103
WI	2005	$5.57	$3.94	1.41	429,000	344,000	59,000	2,222	$2.88	$25.06	$0.106
WI	2006	$4.33	$3.94	1.10	488,000	344,000	258,000	3,341	$3.69	$24.56	$0.112
WI	2007	$4.77	$3.94	1.21	746,000	344,000	643,000	3,618	$3.13	$24.60	$0.113
WI	2008	$5.40	$3.94	1.37	1,389,000	344,000	1,689,000	3,894	$3.55	$24.79	$0.115

Table 3.5

Regression Variable Summary for Multi-State Analysis (57 observations)				
Variable	Mean	Std. Dev.	Min	Max
Non-Module Price/Initial Non Module Price	0.95	0.24	0.55	1.84
State Cumulative Capacity (Watts, 1-Year Lag) / Initial State Cumulative Capacity (Watts, 1-Year Lag)	10.99	19.76	1.00	101.96
State capacity watts installed in current year	10,700,000	29,100,000	59,000	179,000,000
Installation Year	2006	1	2004	2008
Mean System Size (Watts)	4.0	1.2	2.2	7.1
Mean Incentive	$4.20	$1.17	$2.30	$6.28
Mean Electrician's Wage	$26.39	$3.60	$19.29	$32.46
Mean Retail Electricity Price	$0.13	$0.03	$0.08	$0.20

Graph 3.2



Results and Discussion

California Model – Non Module Experience Curve

Estimates for California non-module experience curves that use different cumulative installed capacities are presented in Table 3.6. The progress ratios resulting from the state level specifications range from .84-.92, US capacity specifications progress ratios range from .79-.91, and global capacity progress ratios range from .90-1.11. These are overall consistent with module and non-module progress ratios in the literature, albeit it on the higher ends of estimates. The progress ratio estimates are particularly high using global capacity, although this is not very surprising given that global capacity was not expected to be as a good a predictor of non-module price as state and national capacity. This appears true given the lack of significance in global capacity in 2 of the 3 related models (models 8-10) and the lower R-squareds for the models using global capacity.

Given the limited data, it is difficult to draw conclusions about the rate of learning from the progress ratios.

My key hypothesis is that local capacity is a better predictor of non-module costs than larger geographic boundaries. Consistent with this hypothesis, the models that regress non-module prices on state capacity and additional controls (models 1-4) have a better goodness of fit (higher R-squared) than each of the comparable state and global models (models 5-10). However, it is not possible to determine by comparing the absolute values of the R-squared whether the differences between the models are statistically significant. As such the J-test and Cox-Pearson models are used to test whether it is possible to reject the hypothesis that the state capacity models (models 1-4) are a better predictor than the US capacity and global capacity models.

Before reporting on these tests let me say a word about the significance of the covariates. For the state capacity models, the coefficient on state capacity is significant even with the inclusion of a time trend, current year capacity, and average size variable. The estimates for economies of scale are not precisely estimated.

Table 3.6

Non-Module Price ($/Wp) Learning and Various Geographic Boundaries (1998-2008)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	State	State	State	State	US	US	US	Global	Global	Global
Cum. Capacity State-log, 1-Yr lag	-0.124***	-0.242*	-0.241*	-0.252*						
	(0.0136)	(0.107)	(0.115)	(0.117)						
Installed Year		0.0622	0.0478	0.0604		0.0979	0.0671		-0.0468	-0.0511
		(0.0563)	(0.0685)	(0.0621)		(0.0802)	(0.102)		(0.204)	(0.206)
State Current Year Capacity Installed			0.0263							
			(0.0431)							
Mean System Size,log				0.116						
				(0.326)						
Cum. Capacity U.S. -log, 1-Yr lag					-0.137***	-0.343*	-0.330			
					(0.0164)	(0.167)	(0.180)			
US Current Year Capacity Installed							0.0483			
							(0.0673)			
Cum. Capacity Global-log, 1-Yr lag								-0.149***	-0.0384	0.149
								(0.0164)	(0.471)	(0.504)
Global Current Year Capacity Installed										-0.204
										(0.125)
Constant	-0.0347	-124.4	-95.91	-121.0	-0.0283	-195.8	-134.9	0.0157	93.52	105.8
	(0.0302)	(112.5)	(136.6)	(124.1)	(0.0302)	(160.4)	(202.7)	(0.0338)	(406.6)	(412.2)
Observations	11	11	11	11	11	11	11	11	11	11
Adjusted R-Squared	0.884	0.891	0.880	0.877	0.867	0.880	0.868	0.821	0.800	0.814
Progress Ratio	0.92	0.85	0.85	0.84	0.91	0.79	0.80	0.90	0.97	1.11

The J-test and the Cox-Pearson test for non-nested linear models are used to compare the state capacity model with the US and global capacity models. Since average size is not available for all models and current installed capacity is not significant in the models, I test only specifications 2, 6, and 9.

Comparing the state capacity model (M1) and US capacity model (M2), as reported in Table 3.7, the insignificant p-values of the J-test show neither model can be rejected. However, the Cox-Pesaran significant p-value for Ho:M2 means Model 2 with US capacity can be rejected in favor of Model 1 with state capacity. This suggests that the model with state capacity is a better predictor of non-module prices.

Table 3.7

Competing Models: State and U.S. Capacity
M1:Y=[Non-Module Price, log] X=[Cumulative Capacity State-log, 1-Yr lag; Installed Year]
M2: Y=[Non-Module Price, log] X=[Cumulative Capacity US-log, 1-Yr lag; Installed Year]

J test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	t(7)	-0.85	0.425
H0:M2 / H1:M1	t(7)	1.25	0.252
Cox-Pesaran test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	N(0,1)	0.96	0.169
H0:M2 / H1:M1	N(0,1)	-1.54	0.061

Comparing the state capacity model (M1) and global capacity model (M2), Table 3.8, the significant p-value for the J-test for Ho: M2 suggests the global capacity model can be rejected in favor of the state capacity model. Similarly, the significant Cox-Pesaran test for Model 2 only finds the global capacity model can be rejected in favor of the state capacity Model 1. Both Tables 3.7 and 3.8 suggest that my hypothesis that more local capacity is a better predictor of non-module prices than US and global is correct. However, given the collinearity of inputs and the small sample size these findings are not conclusive. These results are similar when using cumulative solar PV system installations (counts) and time series sensitivities.

Table 3.8

Competing Models: State and Global Capacity
M1:Y=[Non-Module Price, log] X=[Cumulative Capacity State-log, 1-Yr lag; Installed Year]
M2: Y=[Non-Module Price, log] X=[Cumulative Capacity Global-log, 1-Yr lag; Installed Year]

J test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	t(7)	0.95	0.373
H0:M2 / H1:M1	t(7)	2.64	0.034
Cox-Pesaran test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	N(0,1)	0.4	0.344
H0:M2 / H1:M1	N(0,1)	-113.84	0.000

Single-state module experience curve

A similar analysis is conducted for module learning. Module costs are regressed on state, national, and global cumulative PV capacity. As expected, the specifications with global capacity and time trend (8 and 9) have a higher R-squared than the comparable state and national models and models. Global capacity Model 10, which includes the current capacity economies of scale term, unexpectedly has a worse fit than the comparable state and national models (3 and 6). However, neither global capacity nor current capacity is significant in Model 10. The progress ratios for global capacity are inline with the literature. However, similar to the discussion of progress ratios for non-modules, the limited sample size also limits what conclusions can be drawn from these progress ratios about the rate of learning. Table 3.9 presents the regression results.

Although the module regression results are seemingly less conclusive, the J-test and the Cox-Pearson test are used to compare the global module capacity model with the California and US capacity models. In table 3.10, which compares the global capacity model (M1) and state capacity model (M2), the insignificant p-values of the J-test show neither model can be rejected. However, the Cox-Pesaran significant p-values for both models suggest both models can be rejected, although notably the p-value for Model 1 (global) is less significant.

In Table 3.11 comparing the global capacity model (M1) and US capacity model (M2), the insignificant p-values of the J-test suggest neither model can be rejected as the correct specification. However, the Cox-Pearsan test shows Model 2 with US capacity can be rejected in favor of Model 1 with global capacity. This provides some suggestion that global capacity is a better predictor of module prices, but as noted the test findings are weak and not consistent. Moreover, the only control for exogenous technological change included is a time trend. A more flexible control for an exogenous trend, such as a quadratic time trend, could further mute any significant results.

Table 3.9

CA Module Price ($/Wp) Learning and Various Geographic Boundaries (1998-2008)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	State	State	State	State	US	US	US	Global	Global	Global
Cum. Capacity State-log, 1-Yr lag	-0.0443***	0.0917	0.0908**	0.167**						
	(0.0125)	(0.0636)	(0.0338)	(0.0606)						
Installed Year		-0.0720**	0.00435	-0.0594*		-0.104**	0.0392		0.163	0.162
		(0.0312)	(0.0230)	(0.0307)		(0.0419)	(0.0295)		(0.123)	(0.133)
State Current Year Capacity Installed			-0.139***							
			(0.0190)							
Mean System Size,log				-0.815**						
				(0.244)						
Cum. Capacity U.S. -log, 1-Yr lag					-0.0497***	0.169	0.107**			
					(0.0135)	(0.0935)	(0.0421)			
US Current Year Capacity Installed							-0.224***			
							(0.0260)			
Cum. Capacity Global-log, 1-Yr lag								-0.0594***	-0.444	-0.432
								(0.0135)	(0.287)	(0.369)
Global Current Year Capacity Installed										-0.0136
										(0.163)
Constant	-0.0709	143.8*	-6.768	119.4*	-0.0668	207.2**	-75.03	-0.0393	-324.7	-323.9
	(0.0393)	(62.38)	(45.75)	(61.21)	(0.0390)	(83.69)	(58.73)	(0.0336)	(246.2)	(266.3)
Observations	11	11	11	11	11	11	11	11	11	11
Adjusted R-Squared	0.435	0.491	0.929	0.778	0.446	0.517	0.942	0.527	0.569	0.508
Progress Ratio	1.00	1.07	1.06	1.22	0.97	1.12	1.08	0.96	0.74	0.74

Table 3.10

Competing Models: Global Capacity and State Capacity
M1:Y=[Module Price, log] X=[Cumulative Capacity Global-log, 1-Yr lag; Installed Year]
M2: Y=[Module Price, log] X=[Cumulative Capacity State-log, 1-Yr lag; Installed Year]

J test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	t(7)	0.8	0.45
H0:M2 / H1:M1	t(7)	1.34	0.223
Cox-Pesaran test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	N(0,1)	-1.3	0.097
H0:M2 / H1:M1	N(0,1)	-5.62	0.000

Table 3.11

Competing Models: Global Capacity and U.S. Capacity
M1:Y=[Module Price, log] X=[Cumulative Capacity Global-log, 1-Yr lag; Installed Year]
M2: Y=[Module Price, log] X=[Cumulative Capacity U.S.-log, 1-Yr lag; Installed Year]

J test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	t(7)	0.88	0.409
H0:M2 / H1:M1	t(7)	1.17	0.281
Cox-Pesaran test for non-nested models			
	Dist	Stat	P>[Stat]
H0:M1 / H1:M2	N(0,1)	-1.26	0.103
H0:M2 / H1:M1	N(0,1)	-31.5	0.001

Multi-state non-module experience curve

Using an unbalanced panel of 57 annual state and capacity observations from 13 states, OLS is now used to estimate the effect of state experience on annual average non-module prices. The data set (Table 3.4) includes state-year observations from 2004 through 2008 only. All states have five observations except for Minnesota, Nevada, Pennsylvania, and Vermont, which have four observations, and Connecticut and Maryland which have three observations. The larger data set offers more observations, but also the non-module prices may be affected by various state and time varying factors such as labor costs, electricity prices, and building permits. To partially control for these factors state and time fixed effects are included.

Table 3.12 presents the results from a regression of average state non-module costs on state cumulative capacity and control variables. With the inclusion of state and time fixed effects state capacity is not a significant variable. Cumulative state capacity is also not significant using the more parsimonious model (specification 3) that includes time fixed effects and controls for specific state-varying factors such as electricity prices, electrician wages, and average incentives. However, it is interesting that current state capacity installed, which is a proxy for economies of scale, is significant using the more parsimonious model. Given these results I cannot conclude with the pooled panel data set that state capacity is a better predictor of non-module prices than national or global capacity.

Table 3.12

Multi-state Non-Module Price Learning and State Level Capacity			
	(1)	(2)	(3)
	OLS	OLS	OLS
Cum. Capacity State-log, 1-Yr lag	0.0351	0.0374	-0.0303
	(0.0363)	(0.0384)	(0.0456)
Current State Capacity Installed		-0.0172	-0.0741**
		(0.0319)	(0.0347)
Mean System Size,log			0.142
			(0.163)
Mean Incentive,log			-0.133
			(0.148)
Mean Electrician's Wage,log			0.138
			(0.200)
Mean Retail Electricity Price,log			-0.925
			(0.847)
Constant	-0.661***	-0.365	0.585
	(0.136)	(0.532)	(0.718)
Observations	57	57	57
Adjusted R-squared	0.770	0.766	0.351

Specifications 1 and 2 Includes time and state fixed effects.
Specification 3 only includes time fixed effects.

<u>Spillover Analysis</u>

The experience curve model assumes knowledge spillover across states does not exist, i.e. cumulative solar PV capacity and learning in one state does not affect costs in another. However, knowledge spillover can occur across regional and firm boundaries. The exclusion of capacity from states where spillovers originate presents an omitted variable problem in the multi-state analysis. If such knowledge spillovers are present, then a multi-state experience curve analysis may overestimate the effect of an individual state's capacity on in-state non-module costs.

This section demonstrates how one can test for the presence of regional state spillovers and estimate whether spillovers or state capacity (endogenous learning) have a greater effect on a state's solar PV non-module costs. This analysis is conducted with the multi-state data set, although I acknowledge that, given the inconclusive findings of the multi-state analysis, identifying a spillover effect with this data is unlikely. For non-module costs I hypothesize that state spillovers will be positive, but limited since not all knowledge is appropriable. The impact of other state capacity is expected to be greater on a state's non-module costs if the state of interest has a relatively smaller market than neighboring states.

Schaeffer et al. (2004) offer anecdotal evidence of spillovers across European countries non-module prices. They find that although in Europe non-module costs are mainly national, there is some international spillover. Comparing four countries' 2002 non-module prices, they find that although non-module prices were higher in the countries newer to the PV market, the prices for new entrants were still lower than the price for older programs at their onset. I conduct the same comparative analysis for 2004 and 2008 non-module costs for states that are both new entrants and well-established in the PV market. Time in the market is determined to be the number of years the state has had an active PV subsidy program. For the majority of states the market duration is the same. The tables below show the state, market duration, and average non-module price. Observations are sorted by duration in years.

Table 3.13

Program Duration and Non-Module Price Ranking 2004			
Duration	Price rank (lowest to highest)	State	2004 Non-Module Price
7	5	CA	$4.35
3	1	MN	$3.14
3	3	WI	$3.94
3	4	AZ	$4.01
3	8	MA	$5.38
3	10	PA	$6.68
2	2	OR	$3.63
2	7	NJ	$5.26
2	9	NY	$5.46
1	6	VT	$4.84

Table 3.14

Program Duration and Non-Module Price Ranking 2008			
Duration	Price rank (lowest to highest)	State	2008 Non-Module Price
11	2	CA	$4.14
7	1	AZ	$3.61
7	5	MA	$4.99
7	10	WI	$5.40
7	12	MN	$5.78
6	3	CT	$4.94
6	4	OR	$4.94
6	6	NY	$5.00
6	7	NJ	$5.06
5	8	NV	$5.16
5	11	VT	$5.75
4	9	MD	$5.40

A clear pattern between time in the market and non-module cost does not emerge. New entrant states are not necessarily starting with lower non-module prices. The states with the most experience do not consistently have the lowest cost. In 2004, states with the most experience had non-module costs in the middle of the pack of states. The state with one year of experience was also not the most expensive. In 2008, states with the most experience had the lowest costs as well as the highest cost. Comparing states with the same duration in the different time periods, California with seven years experience in

2004 and Massachusetts with seven years in 2008, we see Massachusetts' costs are higher, suggesting that cross-state spillovers may be limited. These findings are consistent with findings by Gillingham et al. (2014) that county average price and time in the market are not well correlated. In an examination of the heterogeneity of PV prices across the United States the authors find that counties with high average prices are sometimes relatively large markets and in other instances very small.

One element missing from this analysis is the likelihood that knowledge is more transferable across neighboring geographies. With geographically contiguous states there is a higher likelihood of fluidity between labor markets and information sharing across regulatory and PV subsidy program administrators. The direction of this knowledge spillover is likely one direction – from a state with larger cumulative installed capacity to a state with lower installed capacity.

Table 3.15

Contiguous States with Cumulative PV Capacity Greater than Origin State 2004-2008	
State	**Contigious States**
AZ	CA
CA	N/A
CT	RI (2004-06),MA,NY
MA	NY
MD	DE,PA
MN	WI
NJ	NY (2004-05)
NV	CA,AZ (2004-07),OR (2004-06),UT (2004-05),ID (2004-05)
NY	NJ (2006-08)
OR	CA,NV (2007-08)
PA	DE (2004),NY,NJ
VT	MA,NY
WI	IL

Table 3.16 presents multi-state regression results for model specifications of the pooled panel data set that include cumulative capacity from contiguous states with greater installed capacity. Contiguous states are used as a measure of exogenous sources of knowledge and as a crude measure for managing the distance decay of information. With this method there is a greater likelihood of under estimating distance decay in the western states that cover larger geographical territories. Conversely, there is a likelihood of omitting relevant state spillovers in the northeastern states by only using contiguous states since there can be a short geographical distance between non-contiguous states.

Table 3.16 Model 2 shows that an individual state's and neighboring state capacity are not significant in a model with time and state fixed effects. This is not surprising given that state capacity is not significant in the initial multi-state regression (Model 1). Given these results, no finding can be made that contiguous state capacity impacts a state's non-module costs.

Table 3.16

Multi-state Non-Module Price ($/Wp) Learning and State Level Capacity with Contiguous State Capacity (2004-2008) Non-Module Price Learning and State Level Capacity			
	(1)	(2)	(3)
Cum. Capacity State-log, 1-Yr lag	0.0351	0.0351	-0.0247
	(0.0363)	(0.0363)	(0.0451)
Current State Capacity Installed			-0.0731**
			(0.0353)
Mean System Size,log			0.161
			(0.174)
Mean Incentive,log			-0.160
			(0.182)
Mean Electrician's Wage,log			0.158
			(0.209)
Mean Retail Electricity Price,log			-0.826
			(0.950)
Neighbor States Cumulative Capacity - log, 1-Yr lag		0.00207	0.00240
		(0.00346)	(0.00619)
Constant	-0.661***	-0.679***	0.476
	(0.136)	(0.142)	(0.816)
Observations	57	57	57
Adjusted R-squared	0.770	0.765	0.339

Specifications 1 and 2 Includes time and state fixed effects.
Specification 3 only includes time fixed effects.

Conclusions and Policy Implications

Using a data set of PV system prices in 13 states, and a longer time series of PV price data for California, some evidence is found that cumulative capacity at the state level is a better predictor of non-module costs than U.S. or global capacity. However, given data limitations it is not possible to determine whether a geographic boundary smaller than state is superior for estimating non-module learning. For example, learning may be best estimated using city level installed capacity or using a weighting of different capacities.

Understanding the influence of a geographic boundary on learning has implications for local policymakers. If non-module costs are influenced by city level actions to expand solar PV capacity, a city council may have more motivation to institute local solar PV subsidies or fast track permitting. However, if the local costs are just as easily affected by expanding state level capacity and subsidies, or are a function of global trends, city regulators may focus instead on directing scarce local resources towards other initiatives.

Since learning rates factor into private and government technology investments and energy planning decisions, estimates for learning geographic boundaries should be regularly updated to reflect changes to the industry that may alter the geographic sphere of influence. For example, certain costs, such as permitting, which are currently influenced by more local capacity developments, may become more influenced by state and national markets as statewide permit models are developed or as industry adopts best practices. Moreover, non-module costs have also declined due to greater systems integration in advance of field deployment. As Harmon (2000) notes, in the past, PV systems have been assembled in the field (versus the factory) from diversely sourced materials and hardware. Trends towards increased standardization of non-module cost components may lead to a smaller portion of total costs subject to a local learning curve.

Experience curve models should be expanded to disaggregate the impact of learning from economies of scale since this may have an impact on what percent of costs declines are appropriable and how impactful state incentives can be. If economies of scale are a greater price driver than endogenous learning, then there is less argument for government support because those cost reductions are fully appropriable, and hence will be pursued by firms. Moreover, if cost declines are being driven purely by economies of scale, these companies will not see cost declines after they reach a minimum efficiency. In this case, overall incentives designed on a composite learning estimate will underperform and not spur expected market cost declines. This paper's proxies for economies of scale, current capacity installed and average system size, are in most specifications not significant. However, further studies should develop better, higher order proxies in order to parse out the relationship between learning-by-doing and economies of scale.

In addition to whether growth in local capacity drives non-module prices, local regulators will also be interested in this paper's discussion of knowledge transfers over jurisdictional boundaries. Further exploration is warranted regarding the possibility that neighboring state capacity may have a greater impact on a state's non-module prices. Neighboring state spillovers may be an explanation for why some states take a "wait and see" approach to demand pull policies and defer to other states, such as a California, to be the first mover with implementing policies to grow clean energy markets. If learning is not all appropriable then this may prove to be a disincentive for some locales to be early technology investors. Such spillovers are particularly disadvantageous to the originating locale when technologies are still far from competitiveness (Bagnall and Boreland, 2008). Further research is warranted on how experience spills over across jurisdictions and whether the prevalence of non-module costs results in unique patterns of information decay or discontinuous jumps in learning.

Arguably there are several other factors besides in-state and neighboring state capacity that affect local installed price. Various works including Gillingham et al. (2014) and Barbose and Dargouth (2015) opine on such factors including labor, incentives, electricity prices, and consumer willingness to pay for solar PV. However, the attempt of this paper is not to explain all the sources of solar PV price declines but to examine how well the experience curve model is suited to forecast overall non-module price declines. This analysis has shown that although they can be informative, experience curve models can also be inaccurate and inconclusive for a variety of reasons including data errors, omitted variables, and model misspecification. In particular, practitioners using experience curve models to forecast solar PV non-module prices should thoroughly consider how the geographic boundary of the market is defined, the relationship between price and cost, possibly endogenous relationship between prices and capacity, and the quality and time series of data available.

Paper 3 Appendix

Table 3.17

Relevant Solar PV Experience Curve Studies							
Authors and Study Year	**Technology Boundary**	**Learning System Geographic**	**Time Period**	**Total years**	**Model factors**	**Dependent Variable and Experience Variable**	**Progress Ratios**
G. Cody and T.Tiedje (1997)	Module	Global	1976-1988	13	price; capacity	$Wp (price); global cumulative sales capacity	0.78
C. Harmon (2000)	Module	Global	1968-1998	31	price; capacity	$Wp (price); global cumulative sales capacity	0.798
IEA (2000)	Module	Global	1976-1996	21	price; capacity	$Wp (price); global cumulative sales capacity	0.84
IEA (2000)	Total PV System (electricity cost)	European Union	1985-1995	11	price; capacity	$Wp (price); global cumulative sales capacity	0.65
V. Parente (2002)	Module	Global	1981-2000	20	price; capacity	$Wp (price); global cumulative sales capacity	0.772 (.798 for 1981-1990 and .774 1991-2000)
G. Schaeffer et al. (2004)	Module	Germany, Netherlands	1976-2001; 1988-2001	26; 14	price; capacity	$Wp (price); national cumulative capacity	.80, .74
G. Schaeffer et al. (2004)	Non-module Balance-of-Systems (total system minus module), limited to residential roof-top grid connected systems less than 100kWp	Europe, Germany, Netherlands	1992-2001	10	price; capacity	German non-module price equal to average of total system price minus module price (from Photex dataset). Dutch non-module price equal to total system price minus estimated module prices.	.80 (Europe), .78 (Germany), .81(Netherlands); .76 (non-inverter, non-module)
M. Papineau (2006)	Module	United States, Germany, Japan, Switzerland	1992-2000	9	cost; capacity; time	Module cost as dollar per watt produced for 15 PV manufacturers (cost, not price); average U.S., German, and Swiss average module price. Experience variables used include country-level cumulative capacity, cumulative electricity	.77 - .90
R. Swanson (2006)	Module	Global	1979-2005	27	price; capacity	$Wp (price); national cumulative capacity	0.80
K. Shum and C. Watanabe (2007)	Non-module Balance-of-Systems (grid-connected distributed PV)	United States	1994-2003	10	price; capacity	$Wp (price); national cumulative capacity	0.825

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