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THE SURPRISING PASS-THROUGH OF SOLAR SUBSIDIES

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ABSTRACT

We estimate the pass-through of solar energy subsidies to solar system prices. Rich micro-level transaction and subsidy data from California indicate that pass-through is remarkably high and differs substantially for consumers who buy versus lease solar systems. Buyers capture nearly the full subsidy, while there is more-than-complete pass-through to lessees. We formalize pass-through over-shifting as an under-utilized test for market power that can also be applied in other contexts. We rule out alternative explanations for over-shifting and conclude that our estimates provide evidence for imperfectly competitive solar markets. Our findings have implications for the distributional effects of energy subsidies.

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1 Introduction

Pass-through of taxes and subsidies—or more generally, cost shocks—to prices plays an important role in economic analysis and policy evaluation across numerous fields of economics. In public economics, pass-through holds a prominent position in the theory of tax incidence and distributional equity (Busse, Silva-Risso and Zettelmeyer 2006; Marion and Muehlegger 2011; Sallee 2011; Weyl and Fabinger 2013; Ito 2015; Ganapati, Shapiro and Walker 2016; Kopczuk, Marion, Muehlegger and Slemrod 2016). The topic has also attracted considerable attention in industrial organization, particularly because pass-through can elucidate the welfare implications from various types of imperfect competition or price discrimination (Fabra and Reguant 2014). While theory predicts and empirical studies confirm—that pass-through rates fall between 0 and 100 percent across a wide range of market structures, those above 100 percent cannot be ruled out theoretically. Such "over-shifting" is not just an economic curiosity. In fact, it is often observed (Besley and Rosen 1999; Delipalla and O'Donnell 2001; Kenkel 2005). More importantly, it can reveal important characteristics about supply, demand, or market power, as theory only rationalizes it under a narrow set of assumptions.

The theory of incidence tells us that markets characterized by various forms of imperfect competition exhibit over-shifting if demand is *very* convex (Seade 1985; Weyl and Fabinger 2013). Existing empirical papers that find over-shifting have therefore discussed the presence of market power as a way to explain their findings, although the connection with theory remains loose.¹ In this paper, we take seriously what theory allows us to infer from over-shifting. Most importantly, we discuss under what conditions over-shifting can be used as a simple and direct test for market power. We provide alternative explanations for over-shifting that do not rely on imperfect competition and argue that they are unlikely to be relevant in many markets. Thus, when judiciously applied, a finding of over-shifting from a straightforward pass-through estimation can serve as evidence of market power, without the need for a structural model of the market in question.

We study these issues in an important empirical setting that, perhaps surprisingly, exhibits pass-through over-shifting: the market for residential solar systems in California, where about half of all U.S. residential solar systems are located (Borenstein 2017). While the impact of solar subsidies on solar system adoptions has been studied (Burr 2014; Hughes and Podolefsky 2015), much less is known about how subsidies are passed through to consumers in the form of lower prices.² The availability of transaction-level microdata makes solar markets well-suited for econometric estimation of subsidy pass-through. Furthermore, beyond its exposition of over-shifting, this market is especially interesting and important in its own right. Governments around the world spent \$120

 $^{^{1}}$ Ritz (2015) points out that the empirical literature has rarely tested whether standard theory can explain specific pass-through patterns. The context discussed is asymmetric pass-through, but the same observation applies for overshifting and other "surprising" patterns of pass-through.

²One of the primary goals of renewable energy subsidies is to (indirectly) address environmental externalities by increasing renewable energy uptake. Another motivation is to correct for non-appropriable learning-by-doing spillovers in solar installation technology (van Benthem, Gillingham and Sweeney 2008; Bollinger and Gillingham 2014). The ultimate beneficiary of the subsidies—i.e., economic incidence—depends on the negotiated subsidy-inclusive solar system price or, in other words, the pass-through of the subsidy.

billion subsidizing renewables in 2014 and \$50 billion on solar alone (International Energy Agency 2016). In the United States, it is not unusual for federal- and state-level incentives to add up to half the total system costs (Gillingham and Tsvetanov 2016).

There are several other unique characteristics that make the solar market particularly interesting from an economist's perspective. First, solar adopters use different system ownership structures namely, host-ownership (HO) versus third-party ownership (TPO)—analogous to buying versus leasing in other markets such as the automobile market. We can therefore estimate how passthrough differs between owners and lessees of the same product. Such comparisons are rare in the literature. Second, the incidence of renewable energy subsidies has been a topic of intense debate. Borenstein and Davis (2016) show that most clean energy tax incentives, including solar subsidies, are highly regressive: the top income quintile has received about 60% of all government support. Another incidence concern is directly about low pass-through. Consumer advocacy groups have accused solar companies of deceptive sales tactics (Greentech Media 2016) and "scamming" homeowners out of their tax credits instead of transferring them to consumers (Watchdog Wire 2014). Third, green subsidies have been criticized for having mixed environmental success due to infra-marginal uptake.³ And lastly, there have been worries about market power in solar markets (Nemet, O'Shaughnessy, Wiser, Darghouth, Barbose, Gillingham and Rai 2017; Pless, Langheim, Machak, Hellow and Sigrin 2017).⁴

We therefore estimate pass-through for both HO and TPO systems, test if they differ and exceed 100%, and if so, if we can take this as evidence that the solar market is imperfectly competitive. To further connect our empirical results with theory, we estimate demand curves in a sufficiently flexible form that allows us to test if our over-shifting finding is consistent with our estimated curvature of demand.

Specifically, we study the California Solar Initiative (CSI) program, the largest state rebate program for solar so far in the United States, which provides lump-sum upfront payments for solar system installations. It started on a multi-billion-dollar budget in January 2007 and was mostly exhausted by mid-2013. An attractive econometric feature of the program is that it involved sharp drops in rebate levels across time and space. We collect solar system-level data on rebates received and system characteristics. The CSI dataset also reports transaction prices for HO systems. However, the reported prices for TPO systems are known to be inconsistently reported, making any analysis of TPO systems using CSI data "fundamentally flawed" (Greentech Media 2013). As such, a novel feature of our analysis is that we construct (post-incentive) prices for TPO systems by calculating the (subsidy-inclusive) net present cost based upon a unique dataset of actual contract terms—such as monthly lease payments, term lengths, upfront payments, and more—agreed upon

 $^{^{3}}$ For example, green subsidies suffer from an additionality problem as some green behavior would occur even in absence of the subsidies. Boomhower and Davis (2014) study how this problem affects the cost-effectiveness of an energy-efficient appliance subsidy program in Mexico and find that about half of the participants would have adopted the technology with no subsidy. Accounting for the additionality problem, Ito (2015) finds that energy conservation subsidies in California did not lead to any conservation in coastal areas (though it did in inland regions).

 $^{^{4}}$ In fact, the U.S. Federal Trade Commission held a workshop in 2016 to examine a variety of solar market competition and consumer protection issues.

between customers and third parties. This entailed sampling and transcribing about 2,000 TPO contracts from 2010-2013 to build a database of TPO contract terms.

We estimate the pass-through rate of the CSI rebate to post-incentive system prices for both HO and TPO customers. Intuitively, the main identifying variation that we leverage comes from large and sudden jumps in rebate levels—across utility territories and over time—relative to smooth price trends. We include a rich set of controls and fixed effects to absorb time-invariant mean differences in prices across regions, panel manufacturers, and installers, as well as smooth weekly quadratic time trends to control for pricing trends such as declining costs and technology uncertainty. As with any empirical study of a specific market, it is important to emphasize that our strategy yields a pass-through estimate local to the California market and for an incentive structured as a direct rebate. With that said, the California solar market is large and often predictive of nationwide or even global solar trends. Therefore, results from California should be of interest to policy makers in many states and countries, who are increasingly interested in how the benefits of green subsidies accrue across different types of consumers and firms.

We find that pass-through is remarkably high and differs substantially for consumers who buy versus lease solar systems. Consumers who buy capture nearly the full subsidy amount—about 86 cents for every dollar increase in subsidies—while there is more-than-complete pass-through to consumers who lease. For lessees, our estimates imply that a \$1 increase in subsidies translates, on average, into a decrease in solar system prices of \$1.65. We thus find that solar subsidies are predominantly (and sometimes even more than fully) passed through to consumers, despite popular claims to the contrary. These results are robust to a variety of sensitivity checks and alternative specifications.

The difference in pass-through rates between buyers and lessees is striking considering both markets offer nearly the same product. Nonetheless, several factors could explain this, such as consumer selection and differences in market structure. Perhaps even more surprisingly, however, is that we find substantial over-shifting in the leasing market. It is natural to ask what explains this over-shifting. As discussed above, imperfect competition combined with "sufficiently convex" demand is a leading explanation, but there exist other conditions under which over-shifting can occur. We formalize pass-through over-shifting as an under-utilized test for market power by outlining alternative explanations that need to be ruled out.

There are several such alternative explanations, but they are uncommon in most markets and certainly unlikely to apply to the solar market. We demonstrate that over-shifting can occur in competitive markets in the presence of Giffen behavior, decreasing marginal costs, nominal pricing rigidities (Conlon and Rao 2016) or—by extending the analysis in Kopczuk et al. (2016)—when firms can inflate their subsidy amounts in a manner unobserved to the econometrician. Such manipulation is nearly impossible in the context of the CSI rebate, although TPO installers have allegedly inflated federal solar tax credits (Greentech Media 2013). These practices do not affect our analysis, however. We also demonstrate that tax salience, while clearly affecting pass-through (Chetty, Looney and Kroft 2009), cannot explain over-shifting in a perfectly competitive market.

Hence, except under conditions that are unlikely in most markets, over-shifting implies imperfect competition.

Finally, we connect the theory of pass-through over-shifting under imperfect competition—which we argue can be only rationalized by sufficiently convex demand in the setting of the California solar market—with an empirical test of demand curvature. While this may seem to be a natural test to perform in an empirical paper that reports pass-through above unity, earlier papers have not explicitly made this connection.⁵ We estimate demand for solar systems in the HO and TPO markets separately and, subject to a range of caveats, find that the curvature of demand in the solar sector appears broadly consistent with the possibility of over-shifting, and perhaps indeed more so for TPO than for HO systems. This is—to the best of our knowledge—the first empirical test of consistency between over-shifting and demand curvature and allows us to provide supporting evidence for our empirical findings, which is crucial to argue for the presence of market power.

There is a rich empirical literature on tax incidence and pass-through, with most papers finding pass-through rates between 0 and 100 percent (see, e.g., Nakamura and Zerom (2010); Goldberg and Hellerstein (2013)). Studies also occasionally document over-shifting. For example, analyses of alcohol taxes (Young and Bielinska-Kwapisz 2002; Kenkel 2005), cigarette taxes (Barzel 1976; Barnett, Keeler and Teh-Wei 1995; Delipalla and O'Donnell 2001), and—in some cases—fuel taxes (Stolper 2016) have found that pass-through exceeds unity.⁶ In fact, more than complete pass-through is actually quite common. Besley and Rosen (1999) study pass-through patterns of transaction taxes for many commodities and find evidence of over-shifting for more than half of them, such as milk, shampoo, and soda.

This paper makes several contributions. It is the first to find over-shifting in clean energy markets, and as one of the few papers to estimate how pass-through differs between owners and lessees of the same product, it is the first to find over-shifting in a leasing context.⁷ Despite the widespread use of leasing, other studies of solar subsidy pass-through have not estimated pass-through for lessees because of data limitations, which we overcome by obtaining TPO contracts (Podolefsky 2015; Dong, Wiser and Rai 2016; Gillingham and Tsvetanov 2016). In fact, to the best of our knowledge, our analysis is the first to differentially estimate pass-through for owners and lessees in any non-property setting.⁸ Perhaps most importantly, we depart from the existing

⁵Several papers (see, e.g., Besley and Rosen (1999) and several more that are cited in the next paragraph) discuss but do not test for—demand convexity as a potential explanation for over-shifting. Stolper (2016) uses measures of market concentration and spatial isolation to explain pass-through patterns, but the paper does not empirically test for demand convexity either.

⁶Marion and Muehlegger (2011) also find that pass-through exceeds unity in gasoline markets, however the result is not statistically distinguishable from 100%. Furthermore, while the main finding in Ganapati et al. (2016) is incomplete pass-through in the U.S. manufacturing context, they note that over-shifting also occurs in industries with inelastic demand and/or relatively high markups.

⁷The paper also contributes to the small but growing literature on subsidy incidence, which has received less attention than tax incidence, particularly in the context of green technologies. Exceptions include Borenstein and Davis (2016) (distributional equity of clean energy tax credits), Kirwan (2009) (agricultural subsidies) as well as West (2004), Sallee (2011), and Beresteanu and Li (2011) (vehicle subsidies).

⁸Busse et al. (2006), Sallee (2011), Busse, Knittel, Silva-Risso and Zettelmeyer (2012), Gulati, McAusland and Sallee (2016), and Kaul, Pfeifer and Witte (2016) estimate pass-through in automobile markets but do not allow for heterogeneous pass-through between buyers and lessees. On the other hand, pass-through has been estimated for

literature by formalizing how an empirical finding of over-shifting can be used to draw conclusions about market power, and by demonstrating how estimating demand convexity can corroborate such a conclusion.

The paper proceeds as follows. Section 2 lays out the theory of pass-through under perfect and imperfect competition. Section 3 details institutional facts about solar energy subsidies and describes the data that we use. Section 4 discusses our empirical strategy and presents solar subsidy pass-through estimation results and their robustness. In Section 5, we discuss alternative explanations of over-shifting besides market power and conclude that they are highly unlikely in our context. Section 6 describes how we flexibly estimate demand to perform an empirical test of consistency between demand curvature and over-shifting theory, and connect this to our pass-through estimates. We conclude in Section 7.

2 Theory of Pass-Through and Market Power

Under the commonly applied simplifying assumptions of perfect competition, upward sloping supply, and downward sloping demand, economic theory predicts that the absolute pass-through of a tax or subsidy to consumers ranges between 0 and 100%. However, (local) pass-through varies substantially according to the slopes and shapes of demand and supply curves, as well as the level of market competition. Pass-through even exceeds 100% under certain conditions, and as previously noted, such "over-shifting" is not unheard of.

To explore how over-shifting can occur, we begin with a discussion of pass-through theory under the standard assumptions of a competitive market with upward sloping supply and downward sloping demand as a baseline. Both consumers and producers take prices as given and choose quantities that maximize their welfare. Let p be the price paid by consumers. Suppliers pay a perunit tax t and therefore receive price p-t. All firms are identical and there is a single market price that equates aggregate demand and competitive supply in equilibrium so that D(p) = S(p-t). We then ask how an increase in the per-unit tax (or analogously, a per-unit subsidy) affects prices. It is common to think of producers directly bearing the cost or benefit and then "passing through" the tax or subsidy indirectly to consumers. We are thus interested in the pass-through rate, $\rho = dp/dt$, or by how much prices paid by consumers rise with a tax increase.

Due to Jenkin (1872), in a competitive market, the pass-through of a tax or subsidy to the prices consumers face is

$$\rho = \frac{1}{1 + \frac{\varepsilon_D}{\varepsilon_S}},\tag{1}$$

where $\varepsilon_D \equiv -(D'p/q)$ is the elasticity of demand, $\varepsilon_S \equiv S'p/q$ is the elasticity of supply and q is

those who lease properties and land in the housing and agricultural sectors. Kirwan (2009) examines how renters of farmland capture agricultural subsidies. Nafari (2017) studies residential property tax incidence in owner-occupied and renter-occupied contexts. None of these papers find over-shifting.

quantity.

Equation 1 is the classic result demonstrating how pass-through in perfectly competitive markets is bounded between 0 and 100% and determined entirely by the relative elasticity of supply and demand. Complete pass-through occurs when either demand is perfectly inelastic or supply is perfectly elastic and zero pass-through occurs when demand is perfectly elastic. In other words, the more inelastic side of the market bears the greater burden of the tax or reaps the larger benefit of the subsidy.

2.1 Pass-Through in the Presence of Market Power

We next consider the case of a monopoly. We assume that the monopolist's profit function is concave in quantity and that the cost, c(q), and demand functions are smooth. Revenues are p(q)q and from this we can find marginal revenues as mr(q) = p(q) + p'(q)q and marginal cost as mc(q) = c'(q). A per-unit tax on producers uniformly raises marginal cost by t, or analogously, a per-unit subsidy on producers uniformly reduces marginal cost by s. As first shown in Bulow and Pfleiderer (1983) and Seade (1985), and more recently in Weyl and Fabinger (2013), pass-through under monopoly can be calculated by solving the monopolist's optimization problem and then finding the rate at which price changes with marginal cost. The monopolist maximizes profits by choosing quantity such that mr(q) = mc(q) + t, and we detail in Appendix A that pass-through can be shown to equal

$$\rho = \frac{1}{1 + \frac{\varepsilon_D - 1}{\varepsilon_S} + \frac{1}{\varepsilon_{ms}}},\tag{2}$$

where ms = -p'q, the marginal consumer surplus, is what consumers earn when quantity expands, and $\varepsilon_{ms} = ms/ms'q$ is the elasticity of the inverse marginal surplus function. This extra component—as we explain below—measures the curvature of the logarithm of demand.

There are two changes from the pass-through formula under perfect competition (Equation 1). First, $\varepsilon_D - 1$ has replaced ε_D , however this does not introduce any new determinants of passthrough.⁹ Second, more importantly, there is the new term containing the inverse elasticity of marginal surplus. This is the key distinctive factor when considering pass-through for a monopolist relative to the case of perfect competition. It is essentially a "convexity parameter" that measures the curvature of (the logarithm of) demand. Weyl and Fabinger (2013) discuss this more extensively, but we can see this using marginal surplus ms = -p'q:

$$(\log D)' = \frac{D'}{D} = \frac{1}{p'q} = -\frac{1}{ms},$$
(3)

where $D \equiv D(p)$ and then

⁹The elasticity of demand is never less than one for the case of a monopoly, and so the appropriate elasticity of demand is relative to unity rather than zero.

$$(\log D)'' = -\frac{1}{\varepsilon_{ms}} \frac{1}{ms^2}.$$
(4)

From Equation 4 it follows immediately that demand is log-concave when $1/\varepsilon_{ms} > 0$ and logconvex when $1/\varepsilon_{ms} < 0$. Log-convexity means that the function is more convex than "normal" convexity. For example, one familiar form of log-convex demand is isoelastic demand such as the case of constant elasticity where $\varepsilon_{ms} = -\varepsilon$. Another useful threshold to bear in mind is that if demand is concave, then $1/\varepsilon_{ms} > 1$, and if it is convex, then $1/\varepsilon_{ms} < 1$. We show this in Appendix A.

This demonstrates how pass-through under monopoly does not just depend on the relative elasticities of supply and demand but also on other parameters that define the shape of the demand curve, specifically on whether demand is concave, convex, or very convex.¹⁰ If we assume constant marginal costs and consider the case of linear demand (i.e., $1/\varepsilon_{ms} = 1$), we can see that Equation 2 reduces to one-half since the component containing elasticity of supply drops out (because the elasticity of supply is infinite). When demand is concave and $1/\varepsilon_{ms} > 1$, pass-through decreases so that it is between 0 and 50%. Alternatively, when demand is convex and $1/\varepsilon_{ms} < 1$, pass-through increases so that it is more than 50%, and it can exceed 100% if demand is "convex enough". More specifically, under linear costs, pass-through exceeds unity if and only if $1/\varepsilon_{ms} < 0$ (i.e., when demand is log-convex).

Figure 1 illustrates pass-through for a monopoly with constant marginal costs facing log-convex demand and thus $\rho > 1$. We also show cases where over-shifting cannot occur in Appendix Figure C.1. Panel A represents the case of perfect competition, where pass-through is strictly between 0 and 100% despite very convex demand. Panel B represents the case of monopoly but with linear demand, where pass-through is always exactly 50%.

The threshold requirement of $1/\varepsilon_{ms} < 0$, or simply $\varepsilon_{ms} < 0$, for pass-through to exceed unity generalizes to other common models of imperfect competition. As shown in Weyl and Fabinger (2013), pass-through under symmetric, imperfect competition is

$$\rho = \frac{1}{1 + \frac{\theta}{\varepsilon_{\theta}} + \frac{\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}},\tag{5}$$

where θ is a conduct parameter ranging between zero for perfect competition and one for a pure monopoly. For many standard models of imperfect competition like Cournot, θ is invariant to changes in q, and thus the term $\theta/\varepsilon_{\theta}$ is absent because $1/\varepsilon_{\theta} = 0$. As such, analogous to the case of the monopoly, pass-through exceeds unity if and only if ε_{ms} is negative.¹¹

 $^{^{10}}$ Bulow and Pfleiderer (1983) and Seade (1985) first emphasized the connection between the elasticity of marginal supply and demand curvature. See also Katz and Rosen (1985), Stern (1987), and Delipalla and Keen (1992) for additional early theory on over-shifting when demand is sufficiently convex in single-product oligopoly models. Anderson, de Palma and Kreider (2001) show that this is also true in an oligopoly with differentiated goods.

¹¹The acceptable range of values for ε_{ms} also should be checked against the second order and stability conditions for the problem to ensure consistency with stable symmetric market equilibrium. We detail these conditions in Appendix A. They imply stricter conditions than $\varepsilon_{ms} < 0$ in order to obtain over-shifting.

Figure 1: Pass-Through Over-Shifting for a Monopolist with Constant Marginal Costs and Constant Elasticity Demand



Note: Figure shows the price effect of a subsidy s on the price p set by a monopolist. MC refers to marginal cost, D to demand, and MR to marginal revenue. The constant elasticity parameter is $\epsilon = -0.5$.

2.2 Over-Shifting as a Test for Market Power

The observation that pass-through can exceed unity is not new. Economists have long understood that over-shifting occurs under many familiar models of imperfect competition when demand is sufficiently convex. However, as we discuss in Section 5, there are other—albeit unlikely—conditions under which pass-through can exceed unity. To the extent that these alternative explanations can be carefully ruled out, however, over-shifting implies the existence of market power.¹² This result has not explicitly appeared in the literature, to our knowledge.

This suggests that estimating pass-through and finding that it over-shifts is an under-utilized test for detecting market power. While more detailed structural modeling can provide important information about market structure and the degree of market power, such an analysis typically imposes large time, data, and resource demands. Alternatively, estimating pass-through of even industry-wide input costs—such as taxes and subsidies—to prices in a partial equilibrium setting, which is often relatively straightforward, can serve as a useful first diagnostic market power test for competition authorities to justify further investigation.

 $^{^{12}}$ Pass-through will not *always* exceed unity when there exists market power (e.g., demand must be sufficiently convex), so finding that pass-through is less than 100% does not imply the absence of market power.

3 Institutional Background and Data

3.1 The California Solar Initiative

The empirical context examined in this paper is solar energy subsidies, a highly prevalent policy tool used to promote clean energy technologies. We study how they are passed through to the solar system prices consumers face in the context of the California Solar Initiative (CSI). In an ideal experiment, we would consider a market characterized by similar installers that offer similar prices to a homogeneous group of potential solar adopters on systems with identical characteristics (size, performance, solar output, design, etc.). We would then randomly vary rebate amounts across consumer groups. Unsurprisingly, actual solar subsidies are not implemented in this way. However, the CSI program design provides unique and exogenous time and cross-sectional variation that allows us to use sudden changes in subsidy levels to identify pass-through with some additional assumptions.

The CSI program took effect on January 1, 2007 with a 10-year planned budget of \$2.167 billion (although the program was mostly exhausted by mid-2013) and was available to the customers of California's three major Investor-Owned Utilities (IOUs): San Diego Gas and Electric (SDG&E), Southern California Edison (SCE), and Pacific Gas and Electric Company (PG&E). The IOUs cover the vast majority of California's ratepayers, making the CSI program representative of California's solar market. Rebate levels started at \$2.50 per watt and "stepped down" over ten pre-determined rates based upon cumulative installed capacity in each IOU service region, declining to \$0.20 per watt over the program lifetime (Figure 2, panel A). This introduced sharp changes in rebate levels (or the per watt value of the subsidy). Figure 2 (panel B) illustrates the CSI rebate level over time and across utilities from 2010 through Q2 2013. Note that the rebate steps change at different times for each IOU.



Figure 2: Variation in CSI Rebate (\$/Watt) Across IOUs and Over Time

⁽a) Rebate Levels as a Function of Cumulative Installed Capacity.

⁽b) CSI Rebate Levels for California's Three IOUs.

Figure 2 conveys the essence of our estimation strategy outlined in Section 4. The sharp changes in rebate levels across IOUs and over time provide us with useful price variation, even when we control for a variety of other potential time trends.

3.2 Host- versus Third-Party Owned Systems and Market Power

As previously described, residential solar customers in California choose to use either HO or TPO, which is analogous to buying versus leasing consumer products in other markets. This choice has direct implications for solar subsidies, which are nominally directed to the system owner. In the case of HO, residential homeowners own the solar system and all output that it generates over its lifetime. On the other hand, under the TPO model, homeowners sign a lease or power purchase agreement (PPA) with a third-party solar company who then owns the system.¹³ In other words, subsidies are directed to homeowners for the case of HO and to solar companies for the case of TPO.

The TPO model for solar was first introduced for residential customers in California in 2007, and it quickly became popular—by 2012, over 70% of new systems in the state were installed using TPO options (Figure 3). Under typical TPO contracts, consumers immediately reap the benefits of installing solar (i.e., electricity bill savings) and avoid taking on debt. Third-party financiers secure investor capital and tax equity to purchase solar systems on behalf of residential homeowners who then lease the systems while incurring little or no upfront cost. The TPO providers also offer additional services such as system monitoring and operations and maintenance over the lease term. At the end of the lease term, homeowners typically have the option to purchase the system at fair market value, renew the lease, or remove the system at no extra cost.

Initially, TPO market traction was largely driven by SolarCity, a firm that offered vertically integrated installation and leasing services. Soon afterwards, competitors like Sunrun began offering TPO contracts as well. Various mergers have taken place over time between financing and installation companies (e.g., Sunrun and REC Solar in 2014), leading to an increasing number of vertically integrated firms. As such, although the industry has seen market entrants over time and many companies offer TPO options, the TPO market is mostly dominated by just a few large firms. On the other hand, there are many small independent installers that offer HO system sales and services.¹⁴

3.3 Solar Subsidy and System Data

We collect solar system-level data from the public CSI database, which includes the total amount of rebate received by residential solar adopters. These data also include system characteristics such as size, location, module type, module manufacturer, module model, number of inverters, and

 $^{^{13}}$ We detail the different types of TPO contract types in Section 3.4 below where we construct price variables.

 $^{^{14}}$ The public CSI data that we use in our study suggest that the top 5 TPO companies were responsible for about 56% of TPO installations from 2010 through Q2 2013. In contrast, the top 5 HO companies were responsible for just 17% of HO installations.



Figure 3: Trend in CSI Rebate Applications by Business Model in California, 2010-Q2 2013

Note: The drop in the spring of 2013 reflects that rebates were exhausted for customers in Pacific Gas & Electric's territory at the end of April 2013.

installer. This provides us with a rich set of controls. We include additional controls by matching our system-level data to census tract-level demographic data. Details are provided in Appendix B.1.

We include only residential systems in our sample and define the rebate date as the "first reservation request review date", since rebate amounts are determined when the rebate reservation is made as opposed to when the project is completed. Following Hughes and Podolefsky (2015), we view the reservation date as the best approximation of the customer's decision timing. We begin our sample in 2010 due to TPO contract data availability and we end our sample at the end of Q2 2013. This is when subsidy rates had become very low (or exhausted) across IOUs.

The total CSI rebate amounts listed in the database are determined by the rebate rates that existed at the time the customer made a reservation through their IOU as well as the system and geographical characteristics that contribute to expected system performance. The rebate application process requires submitting information on system characteristics that determine performance, such as module type, inverter type, system size, installation location, site shading, system orientation, etc. These characteristics determine the system's "design factor", or the expected electrical output of the solar system relative to a reference system. The design factor is multiplied by the rebate rate to find the total subsidy amount. This amount is reported back to the customer, and once the system is installed and connected to the grid, the solar system owner receives a check for the total subsidy amount. We describe a few other steps we took to prepare the data in Appendix B.1.

3.4 System Price Data

The effective price of a solar system to a consumer reflects government incentives. These are either factored into the transaction price paid to the installer if the company receives the subsidy, or alternatively, the consumer receives a rebate directly from the government that should be subtracted from the transaction price. Under TPO, contractors negotiate contract terms based upon the rebate they receive and presumably pass-through subsidies to consumers to some degree in the form of more favorable contract terms.

The price measure used in this paper, post-incentive price, is the transaction price inclusive of cash rebates and other incentives. Our primary challenge is in obtaining an equivalently measured post-incentive price for TPO and HO systems. The CSI dataset includes "total reported cost" without incentives. This is considered a reliable measure for HO systems, so the post-incentive price for HO consumers is simply the reported total cost minus incentives. These include the CSI incentive amount as well as a pre-existing federal incentive, the federal investment tax credit (ITC), which provides a 30% tax credit to all solar PV system owners.

We do not observe the actual ITC for each consumer. To overcome this, we derive the implied ITC by assuming that it is fully monetized.¹⁵ For an HO system, the CSI rebate is considered a price reduction for tax credit purposes. Thus, the ITC applies to the after-rebate net price paid by the customer, calculated as

$$ITC_{HO,i} = 0.3 * (TC_{HO,i} - CSI_{HO,i}), \tag{6}$$

where $ITC_{HO,i}$ is the federal ITC received by HO consumer *i*, $TC_{HO,i}$ is the total system cost reported in CSI, and $CSI_{HO,i}$ is the total CSI rebate amount received. The post-incentive price for HO consumers is then the total reported cost minus CSI and ITC.

Importantly, the total costs in the CSI database for TPO systems are reported inconsistently. It has been widely recognized that any analyses of CSI data that use reported costs as a proxy for fair market value of TPO systems are "fundamentally flawed" (Greentech Media 2013). Therefore, deriving a post-incentive price faced by TPO consumers requires information on the actual TPO contract terms agreed upon between customers and third parties. As such, we construct the post-incentive price for TPO consumers by calculating the (subsidy-inclusive) net present cost (NPC) based upon actual contract terms. This requires data on monthly lease payments or power purchase agreement (PPA) rates, estimated solar production (for PPAs), contract term length, upfront payments, and whether an annual escalation rate is applied.

We obtained a non-disclosure agreement with the California Public Utilities Commission to gain access to residential TPO contracts signed during 2010-2013. We sampled about 2,000 of the contracts following a stratified sampling strategy described in Appendix B.1. We manually

¹⁵It is possible that the cost of the system reported to the CSI is not the cost reported on tax forms. Furthermore, the credit is non-refundable and cannot be carried forward beyond 2016. As such, the customer must have enough tax liability to absorb the credit. Our calculation follows Borenstein (2017) and assumes that the ITC is fully monetized. This likely overstates its value somewhat (Borenstein 2017).

transcribed this set of contracts to build a unique database of TPO contract terms. This provided us with the relevant information needed to calculate the NPC of each contract based upon a standard discounted cash flow methodology. We assume a 7% discount rate as a baseline (see Section 4.3 for sensitivity analysis around this assumption), and calculate the NPC as follows:

$$NPC_{i} = U_{i} + \sum_{y=1}^{t} \frac{payment_{iy}}{(1+d)^{y}},$$
(7)

where U_i is the upfront payment for system *i*, $payment_{iy}$ is the total annual payment in year *y*, *d* is the real discount rate, and *t* is the number of years on the contract term.

For leases, annual payments are derived from monthly payment amounts and escalation rates. For PPAs, annual payments are calculated based upon the PPA rate as well as estimated year one production (also provided in the contract) and assuming a 0.5% annual output degradation rate over the contract term length (following Jordan and Kurtz (2013)).¹⁶ For prepaid TPO systems—the case where a TPO agreement was signed but the consumer pays for all monthly payments upfront—the NPC is simply the amount paid upfront.

Like HO consumers, TPO installers were eligible for other existing incentives as well; TPO installers can take advantage of an accelerated depreciation scheme, the Modified Accelerated Cost Recovery System (MACRS), in addition to the ITC. However, there is no need to net out such incentives from the NPC in order to obtain a post-incentive price as we do in the case of HO systems, because the TPO installers receive all subsidies directly and these are embedded in the final contract price offered to consumers. In other words, the NPC for TPO consumers is already a post-incentive price.

Figure 4 illustrates how post-incentive prices evolved in the California solar market, both for HO and TPO consumers. They decline gradually, but more so for HO than for TPO. Given the simultaneously declining path of CSI rebates, pre-incentive prices decrease more rapidly. The difference in time trend for HO versus TPO is one indication that these markets are different and further motivates why we allow pass-through and time trends to vary across contract types.

Table 1 presents summary statistics of our data from 2010 through Q2 2013, including the CSI rebate amounts, post-incentive prices, other system characteristics, and demographics. In general, differences for HO and TPO systems are statistically significant but they are relatively modest in terms of their economic magnitudes. Post-incentive prices and CSI rebates tend to be somewhat lower for TPO consumers, which is consistent with HO systems being more prevalent in the early years of our sample when prices and rebates were higher. There are no demographic differences that stand out; the similar (and high) median household incomes for both types of customers suggest that they are similar populations.

 $^{^{16}{\}rm The}$ NPC of PPAs should be interpreted as an "expected" NPC since the payments are based upon estimated production.



Figure 4: Post-Incentive Price (\$/Watt) Trends for TPO vs. HO

Table 1: Descriptive Statistics of Final Sample, 2010-Q2 2013.

| | Means | | | Standard | Deviations |
|-------------------------------------|-----------|-----------|----------------|---------------|------------|
| | НО | TPO | Difference | НО | TPO |
| | (1) | (2) | (3) | (4) | (5) |
| A. System Characteristics | | | | | |
| CSI rebate (\$/watt) | 0.505 | 0.386 | \$0.119*** | 0.398 | \$0.342 |
| CSI rebate (\$) | \$2,403 | \$2,195 | \$208*** | \$2,261 | \$2,253 |
| Post-incentive price (\$/watt) | \$4.13 | \$3.42 | \$0.71*** | \$1,379 | 0.920 |
| Post-incentive price (\$) | \$18,975 | \$18,931 | \$44 | \$7,905 | \$7,408 |
| System size (watts) | 4,903 | $5,\!648$ | -745*** | 2,096 | 1,909 |
| System has more than one inverter | 42.8% | 18.9% | $23.9\%^{***}$ | 49.5% | 39.2% |
| | | | | | |
| B. Demographics | | | | | |
| Bachelor's degree or higher $(\%)$ | 41.0% | 38.0% | $3.0\%^{***}$ | 18.9% | 18.4% |
| Less than high school education | 9.5% | 10.2% | -0.7%*** | 9.0% | 9.0% |
| education, age 18 and older $(\%)$ | | | | | |
| Population density (per sq. mile) | 4,209 | 3,734 | 475*** | $5,\!630$ | 4,122 |
| Housing unit density (per sq. mile) | $1,\!631$ | 1,349 | 282^{***} | $2,\!642$ | $1,\!666$ |
| Median age of household head | 41.3 | 39.8 | 1.6^{***} | 7.4 | 7.4 |
| Median number of household members | 2.36 | 2.48 | -0.12*** | 0.50 | 0.50 |
| Family households (%) | 73.1% | 76.3% | -3.2%*** | 12.8% | 11.0% |
| Median number of family | 2.78 | 2.86 | -0.09*** | 0.42 | 0.35 |
| household members | | | | | |
| Percent owners of all households | 52.4% | 52.9% | -0.5% | $5.5\%^{***}$ | 5.5% |
| Median household income (\$) | \$89,752 | \$90,705 | -953 | \$33,811 | \$33,993 |
| Median house value (\$) | \$520,178 | \$472,906 | \$47,272*** | \$250,326 | \$243,172 |

Notes: Demographics are at the census tract level. Dataset contains 32,125 HO observations and 1,306 TPO observations. Asterisks denote *p < 0.10, **p < 0.05, ***p < 0.01.

4 Empirical Pass-Through Results

4.1 Econometric Framework

To understand how solar subsidies are passed through to consumers, we estimate the effect of the CSI rebate on post-incentive system prices using the following linear specification that allows for heterogeneous effects between TPO and HO consumers:

$$p_i = \alpha + \beta_1 rebate_i + \beta_2 rebate_i * TPO_i + \beta_3 TPO_i + \mathbf{X}_i \phi + \gamma_j + \delta_k + \varphi_u + \omega_z + \lambda_c + \mu_t + \varepsilon_i, \quad (8)$$

where p_i is the post-incentive price (\$/watt) of system *i* (henceforth "price"), $rebate_i$ is the CSI rebate (\$/watt), and TPO_i is a business model indicator (1 if the system is TPO; 0 otherwise). \mathbf{X}_i includes control variables, γ_j are module manufacturer fixed effects, δ_k are county fixed effects, φ_u are IOU territory (utility) fixed effects, ω_z are module model fixed effects, λ_c are installer fixed effects, μ_t are contract type specific weekly quadratic time trends, and ε_i is an error term.

Importantly, we adjust the CSI rebate to correct for its interaction with pre-existing federal incentives (ITC and MACRS) for which solar customers were eligible throughout the sample period. These subsidies mechanically reduce the value of the CSI rebate amount. For example, for HO systems, the ITC is calculated as 30% of the after-rebate net consumer price. Hence, a one-dollar increase in the CSI rebate is effectively worth only 70 cents, because the extra CSI dollar decreases the value of the ITC by 30 cents. We thus need to multiply the CSI rebate by a correction factor of 0.7 in order to interpret our pass-through coefficient as the price impact of a full one-dollar subsidy increase. More details, including a similar correction for TPO systems, can be found in Appendix B.2. Other papers estimating solar subsidy pass-through have not addressed this issue.

We include a rich set of fixed effects to control for time-invariant mean differences in prices across IOUs, counties, module models, module manufacturers, and installers. We reduce dimensionality by creating installer fixed effects for any installer that captures more than 1% of the TPO market or more than 1% of the HO market.

Controls include three system characteristics that could impact price: system size, squared system size, and a dummy if more than one inverter is installed.¹⁷ We flexibly control for system size because larger systems may be cheaper even on a per watt basis. Similarly, inverters are an important component of the cost of the system. In our controls, we also include census tract level mean demographic and housing characteristics that could affect price for numerous reasons, such as strategic marketing efforts by installers or negotiation skills by consumers. These include median household income, median house value, housing density, population density, median age, and percentage of the population with a bachelors degree or higher.

Lastly, our identification strategy uses smooth weekly quadratic time trends for each contract type (HO, lease, PPA, or prepaid lease).¹⁸ These trends control for general pricing trends such

¹⁷Size is measured as the effective system size, or "CSI rating", which is a location- and system-adjusted capacity measure (in watts).

¹⁸Table 5 shows that a less flexible specification that allows time trends to vary only for HO vs. TPO yields very similar results.

as declining costs and technological progress. Intuitively, the main identifying variation that we leverage comes from large and sudden jumps in CSI rebate levels—across utilities and over time—relative to smooth price trends (see Figure 2, panel B). One might think that the sharp rebate level changes lend naturally to a regression discontinuity design. However, the transparency of the rebate level changes induced a timing response, which complicates the interpretation of an regression discontinuity estimation.¹⁹

4.2 Main Results

Table 2 presents our main results, which measure the effect of a \$1/watt rebate level increase for HO and TPO consumers on post-incentive prices. Columns 1-7 gradually add more flexible controls.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|-------------------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| Incentive | 0.349^{***} | 0.360^{***} | -0.172^{*} | -0.415*** | -0.532*** | -0.581*** | -0.860*** |
| | (0.116) | (0.084) | (0.089) | (0.078) | (0.072) | (0.071) | (0.061) |
| Incentive * $1[system = TPO]$ | -1.112^{***} (0.234) | -0.887^{***} (0.220) | -1.138^{***} (0.222) | -1.054^{***} (0.224) | -1.011^{***} (0.217) | -1.066^{***} (0.220) | -0.785^{***} (0.212) |
| 1[system = TPO] | -0.612^{***} (0.190) | -0.548^{***} (0.173) | -0.492^{***} (0.174) | -0.070 (0.169) | -0.164 (0.176) | -0.164 (0.176) | -0.265 (0.170) |
| Controls | | х | х | х | х | х | x |
| Utility FE | | | х | x | х | х | x |
| Manufacturer FE | | | | x | х | x | х |
| Module FE | | | | | х | x | х |
| County FE | | | | | | x | х |
| Installer FE | | | | | | | х |
| Quadratic contract type time trends | х | х | х | x | х | x | х |
| Number of observations | 34,763 | 33,431 | $33,\!431$ | 33,431 | $33,\!431$ | 33,431 | 33,431 |

Table 2: Main Estimates: Pass-Through of Solar Subsidies

Notes: Dependent variable is the post-incentive system price per watt. Data cover systems installed in California for consumers who applied for the CSI rebate during the period 2010-Q2 2013. Controls include system size, squared system size, a dummy if there is more than one inverter, and census tract level demographics. A 7% discount rate is assumed for the net present cost and MACRS calculations. Standard errors clustered by zip code. Asterisks denote *p < 0.10, **p < 0.05, **p < 0.01.

Throughout all specifications, we find that the difference in pass-through between TPO and HO consumers is large and highly statistically significant, but to more accurately estimate the pass-through to HO consumers we need detailed controls. In our preferred specification that includes all controls and fixed effects (column 7), the pass-through rate is 86% for HO and 165% for TPO.²⁰ Pass-through for TPO is statistically and economically greater than 100%, providing evidence

¹⁹The timing response is visible as "bunching" of CSI rebate reservations just prior to a subsidy change. See Appendix C.2 and Appendix Figure C.2 for further illustration and discussion, and Section 4.3 below for a robustness check to rule out that this type of bunching impacts our main results.

²⁰Our estimate for HO systems is similar to pass-through rates found in other studies of HO markets, providing additional confidence in our estimation strategy. Gillingham and Tsvetanov (2016) find a pass-through rate of 84% in Connecticut and Dong et al. (2016) find nearly 100% pass-through in California. Podolefsky (2015), however, finds a very low pass-through rate for a different types of incentive (the solar investment tax credit). None of these studies examine TPO markets.

of substantial pass-through over-shifting. In contrast, pass-through for HO is statistically less than 100%, implying incomplete but still high pass-through. The coefficient estimate on the TPO indicator captures time-invariant factors that account for price differences between TPO and HO. It is not statistically significant once we include enough controls and fixed effects.

In summary, our main estimates show that pass-through for solar systems is strikingly high. They also demonstrate significant over-shifting for TPO systems. We discuss and interpret these findings in more detail in the following sections, but first we turn to showing the robustness of our estimates.

4.3 Robustness Checks

One critical assumption of our identification strategy is that price trends are smooth over time except for sudden changes in the CSI rebate. To be more confident that our results are not sensitive to the degree of flexibility of the time trend, we estimate additional specifications with more and less flexible contract type specific weekly time trends. These results are presented in Table 3.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-------------------------------------|-----------|-----------|-----------|----------------|----------------|-----------|
| Incentive | -0.875*** | -0.860*** | -0.885*** | -0.862*** | -0.893*** | -0.832*** |
| | (0.058) | (0.061) | (0.060) | (0.060) | (0.061) | (0.061) |
| | | | | | | |
| Incentive * $1[system = TPO]$ | -0.929*** | -0.785*** | -0.732*** | -0.701^{***} | -0.784^{***} | -0.773*** |
| | (0.230) | (0.212) | (0.210) | (0.210) | (0.213) | (0.206) |
| 1[avetem - TPO] | 0.019 | 0.265 | 0 700*** | 0 837*** | 0.450 | 0 752*** |
| I[System = II O] | -0.012 | (0.170) | -0.700 | (0.927) | (0.202) | -0.755 |
| | (0.155) | (0.170) | (0.189) | (0.237) | (0.292) | (0.220) |
| Controls | Х | Х | Х | Х | х | х |
| Utility FE | х | х | х | х | х | x |
| Manufacturer FE | x | х | х | x | x | x |
| Module FE | x | х | х | х | х | x |
| County FE | x | х | х | x | x | x |
| Installer FE | x | х | х | х | х | x |
| Linear contract type time trends | х | | | | | |
| Quadratic contract type time trends | | x | | | | |
| Cubic contract type time trends | | | х | | | |
| Quartic contract type time trends | | | | х | | |
| Quintic contract type time trends | | | | | х | |
| Quarter*year*contract type FE | | | | | | x |
| Number of observations | 33,431 | 33,431 | 33,431 | 33,431 | 33,431 | 33,431 |

 Table 3: Sensitivity of Pass-Through Estimates to Time Trend Flexibility

Notes: Dependent variable is the post-incentive system price per watt. Data cover systems installed in California for consumers who applied for the CSI rebate during the period 2010-Q2 2013. Controls include system size, squared system size, a dummy if there is more than one inverter, and census tract level demographics. A 7% discount rate is assumed for the net present cost and MACRS calculations. Standard errors clustered by zip code. Asterisks denote *p < 0.10, **p < 0.05, **p < 0.01.

We find that the magnitude and significance of our estimates are stable at different levels of time trend flexibility (columns 1-5; baseline estimates in column 2). We also add a specification in which weekly polynomial time trends are replaced with quarter by year fixed effects for each contract type (column 6). This hardly affects our pass-through estimates.

We also test if our estimates are sensitive to the discount rate assumption used in the TPO contract NPC calculations. We estimate pass-through assuming discount rates ranging from 2% to 12%. The estimates are stable across specifications (see Table 4; baseline estimates in column 3).

| | (1) | (2) | (3) | (4) | (5) |
|-------------------------------------|-------------|-------------|-------------|-------------|--------------|
| | 2% Discount | 4% Discount | 7% Discount | 9% Discount | 12% Discount |
| | Rate | Rate | Rate | Rate | Rate |
| Incentive | -0.862*** | -0.861*** | -0.860*** | -0.859*** | -0.859*** |
| | (0.062) | (0.061) | (0.061) | (0.060) | (0.060) |
| Incentive * $1[system = TPO]$ | -0.891*** | -0.839*** | -0.785*** | -0.759*** | -0.729*** |
| | (0.317) | (0.261) | (0.212) | (0.194) | (0.180) |
| 1[system = TPO] | 0.667** | 0.228 | -0.265 | -0.514*** | -0.803*** |
| | (0.263) | (0.214) | (0.170) | (0.153) | (0.140) |
| Controls | | | | | |
| Controls | х | х | х | х | х |
| Utility FE | х | х | х | х | х |
| Manufacturer FE | х | х | х | х | х |
| Module FE | х | х | х | х | х |
| County FE | х | х | х | х | х |
| Installer FE | х | х | х | х | х |
| Quadratic contract type time trends | х | х | х | х | х |
| Number of observations | $33,\!431$ | $33,\!431$ | $33,\!431$ | $33,\!431$ | $33,\!431$ |

Table 4: Sensitivity of Pass-Through Estimates to the Discount Rate

Notes: Dependent variable is the post-incentive system price per watt. Data cover systems installed in California for consumers who applied for the CSI rebate during the period 2010-Q2 2013. Controls include system size, squared system size, a dummy if there is more than one inverter, and census tract level demographics. A 7% discount rate is assumed for the net present cost and MACRS calculations. Standard errors clustered by zip code. Asterisks denote *p < 0.10, **p < 0.05, **p < 0.01.

We perform a number of further robustness checks in Table 5. Column 1 shows that the estimates are almost identical when we include time trends that differentiate between HO vs. TPO only, rather than allowing separate trends for leases, PPAs and prepaid leases. In column 2, we account for the possibility that there are solar panel manufacturer-specific time-varying factors that affect pricing, for example for foreign-based vs. domestic manufacturers. The results show that our results are robust to interacting manufacturer and contract type specific time trends.

We further explore robustness by using propensity score matching to compare differences in pass-through between matched TPO and HO systems sold in similar markets. We match on the system and census tract level demographic controls used above as well as the utility region. The results are similar to the main estimates, with pass-through for HO slightly below 100% and overshifting for TPO (column 3). The degree of over-shifting for TPO is slightly lower than in our baseline specification.

Furthermore, it is possible that our pass-through estimates vary over time because HO installations are front-loaded to earlier years in our sample and market conditions can change over time. We therefore ran a version of our regression in which we allow pass-through to vary in the first and second half of the sample period. Column 4 shows that our main conclusions hold for both time periods. In the second period, pass-through for HO is slightly lower than in the first period. For TPO, pass-through is somewhat higher.

Overall, the various sensitivity and robustness checks in Tables 3-5 show that our results are stable across specifications in significance and magnitude. We consistently find pass-through below 100% for HO and above 100% for TPO. This is reassuring and provides additional confidence in our pass-through estimates.

| | (1) | (2) | (3) | (4) |
|--|-------------|-----------------|------------------|------------|
| | HO vs. TPO | Manufacturer by | Propensity Score | Two Time |
| | Time Trends | Contract Type | Matching | Periods |
| | | Time Trends | | |
| | | | | |
| Incentive | -0.862*** | -0.820*** | -0.940*** | -0.862*** |
| | (0.061) | (0.060) | (0.163) | (0.060) |
| Incentive $* 1$ [system $- TPO$] | -0.823*** | -0.610*** | -0.507* | -0 717*** |
| | (0.258) | (0.213) | (0.262) | (0.219) |
| | (0.200) | (0.210) | (0.202) | (0.210) |
| Incentive * 1[second half] | | | | 0.222*** |
| | | | | (0.071) |
| | | | | |
| Incentive * $1[system = TPO] * 1[second half]$ | | | | -0.365 |
| | | | | (0.392) |
| 1[system - TPO] | -0.173 | -0 422** | -0.410* | -0 333* |
| $1[3y_{30}] = 110]$ | (0.204) | (0.187) | (0.225) | (0.181) |
| | (0.204) | (0.101) | (0.220) | (0.101) |
| Controls | х | х | х | х |
| Utility FE | х | х | х | х |
| Manufacturer FE | х | х | х | х |
| Module FE | х | х | х | x |
| County FE | х | х | х | x |
| Installer FE | х | х | х | x |
| HO vs. TPO quadratic time trends | x | | | |
| Manufacturer by contract type | | х | | |
| quadratic time trends | | | | |
| Quadratic contract type time trends | | | х | x |
| Number of observations | $33,\!431$ | 33,431 | 33,431 | $33,\!431$ |

 Table 5: Robustness Checks of Pass-Through Estimates

Notes: Dependent variable is the post-incentive system price per watt. Data cover systems installed in California for consumers who applied for the CSI rebate during the period 2010-Q2 2013. Controls include system size, squared system size, a dummy if there is more than one inverter, and census tract level demographics. A 7% discount rate is assumed for the net present cost and MACRS calculations. Matching in column 3 based upon the controls listed above and the utility region. Standard errors clustered by zip code. Asterisks denote *p < 0.10, **p < 0.05, ***p < 0.01.

In a final robustness exercise, we check that our estimates are not confounded by the "bunching" effect discussed in footnote 19 above. As rebates drop around pre-specified thresholds in terms of total installed capacity within an IOU-region, solar customers and installers may rush to get their rebate applications submitted before the date they expect the rebate level to drop. Appendix Figure C.2 shows that such bunching was indeed present, consistent with Hughes and Podolefsky (2015).

To examine how this bunching affects our estimates, we estimate pass-through based upon samples that omit observations within a symmetric window of 4 weeks, 8 weeks, and 12 weeks around the rebate level drop dates for each IOU. Appendix Table C.1 shows that this does not change our conclusions in any way. Pass-through for HO is almost identical to our main estimate in Table 2 (83-84% compared to 86%). The estimates for TPO are somewhat higher (171-194% compared to 165%). Overall, TPO pass-through is still consistently much higher than HO pass-through and statistically greater than 100%.

5 Alternative Explanations

In Section 2, we discuss how the presence of market power can theoretically explain over-shifting. While there are several alternative explanations for more-than-complete pass-through besides imperfect competition, such conditions are uncommon in most markets and could be considered special cases. We discuss them in this section and argue that they are also unlikely to occur in solar markets. We also discuss how one phenomenon that is widely known to affect pass-through, tax salience, *cannot* explain over-shifting in a competitive market.

Giffen Behavior.—Equation 1 demonstrates how Giffen behavior, $\varepsilon_D > 0$, could lead to overshifting. However, Giffen goods are strongly inferior goods (i.e., goods in very high demand by low-income consumers), while the household income among solar adopters strongly suggests that solar systems are luxury goods (Table 1). Furthermore, empirical evidence of upward sloping demand is extremely sparse; the literature so far has found evidence exclusively in the developing country context.²¹ For the U.S. residential solar market, empirical estimates of the price elasticity of solar systems show that solar markets are indeed characterized by the expected downward sloping demand curves (e.g., Gillingham and Tsvetanov (2016)). Our own demand elasticities in Section 6, while admittedly imprecise, confirm this finding. We conclude that Giffen behavior is unreasonable for solar markets and indeed highly unlikely in most markets.

Salience.—We know that tax salience affects pass-through from Chetty et al. (2009). However, we now show that salience cannot explain over-shifting under perfect competition. Chetty et al. (2009) show that consumers underreact to taxes that are not salient.²² In their experiment, consumers make purchasing decisions based on the pre-tax posted price, but they end up paying a tax-inclusive price at the supermarket's register. Analogously, consumers may underreact to subsidies if they are not salient.

To investigate whether tax (or subsidy) salience can explain over-shifting, we first discuss how imperfect salience affects pass-through. We follow Chetty et al. (2009)'s derivation of pass-through

 $^{^{21}}$ Until Jensen and Miller (2008)'s demand estimation for dietary staples among extremely poor households in China, there were no well-identified empirical papers demonstrating the existence of markets with upward sloping demand. To our knowledge, the existence of Giffen behavior has not been shown to exist in any other markets since, either.

 $^{^{22}}$ We follow Chetty et al. (2009) in using the term "tax salience" to refer to the visibility of the tax-inclusive price.

that allows for salience effects (and other optimization errors) with respect to taxes and refer to that paper for details. Let \hat{p} denote a good's pre-tax price and assume t is a per-unit tax so that the tax-inclusive price is $p = \hat{p} + t$. Z denotes wealth of the representative consumer. Under perfect competition, the market-clearing price \hat{p} satisfies $D(\hat{p}, t, Z) = S(\hat{p})$ and implicit differentiation of this yields the pass-through to consumers as

$$\frac{dp}{dt} = 1 + \frac{d\hat{p}}{dt} = \frac{\varepsilon_S + (1 - \eta)\varepsilon_D}{\varepsilon_S + \varepsilon_D},\tag{9}$$

where η is the degree to which agents under-react to the tax t.²³ When a tax or subsidy is perfectly salient, or $\eta = 1$, Equation 9 is identical to the standard pass-through Equation 1 under perfect competition. When $\eta = 0$ and the tax or subsidy is fully non-salient (i.e., consumers completely ignore the tax or subsidy), a new positive term enters the numerator of the pass-through formula. Hence, the pass-through of a tax increases as salience decreases. Since $\frac{dp}{dt} = -\frac{dp}{ds}$, the pass-through of a subsidy also increases with lower salience—consumers underreact to the subsidy and their ex-post subsidy-inclusive price ends up being lower.

From Equation 9 it becomes clear that salience cannot explain over-shifting in a perfectly competitive market; pass-through will be strictly bound between 0 and 100% for $0 \le \eta \le 1.^{24}$ As such, even under imperfect salience, over-shifting still implies imperfect competition.

Nonetheless, although limited salience cannot explain over-shifting, differences in salience between HO and TPO could provide one of many possible reasons why their pass-through rates differ. We now argue that limited salience is unlikely to describe either solar market in California. First, consider the case of TPO, where companies receive the CSI rebates, list rebate amounts on customer TPO contracts, and then quote final contract terms so that consumers see prices that fully embed the subsidies. This makes the tax-inclusive price in this market fully salient to consumers. They are not surprised ex-post by a rebate check that they receive some time after purchasing the solar system.

Next, consider the case for HO customers. In this market, the host owner receives the rebate check directly (ex-post) in some cases; in other cases the company receives it and then quotes a subsidy-inclusive price (as well as the subsidy amount) to the customer. In the first case, consumers pay pre-subsidy prices. In the second case, consumers pay subsidy-inclusive prices, analogous to the case for TPO consumers. It is the first type of HO transactions in which CSI subsidies could be less than fully salient.²⁵ However, as the rebate amount is always reported to the consumer at

²³Chetty et al. (2009)'s original formulation multiplies the ε_S terms by p/\hat{p} , however we follow most of the literature in assuming small changes in the tax/subsidy for consistency with our main analysis in Section 2, and thus $p/\hat{p} \approx 1$.

²⁴Although $\eta < 1$ for most commodity taxes, $\eta > 1$ can occur if consumers overestimate tax or subsidy rates, as appears to occur for opaque estate tax systems (Slemrod 2006). However, this case of the tax or subsidy being "super salient" would decrease pass-through even more to some amount less than pass-through under full optimization. Furthermore, $\eta < 0$ would imply that consumers implicitly count on a tax actually being a subsidy, which we rule out as unreasonable.

²⁵However, if subsidy-inclusive prices are indeed less salient for HO consumers than for TPO consumers, we would expect higher pass-through for HO systems. This is the opposite direction from what we find empirically in Section 4

the time of purchase, the calculation method is transparent and easily verifiable, and the subsidy is large, it would be highly surprising if not all buyers and installers were aware of it. Thus, imperfect salience is highly unlikely in both HO and TPO markets.

Subsidy Manipulation.—Another factor that can explain differences in pass-through rates is a differential ability of firms to evade taxes. We use Kopczuk et al. (2016)'s framework to argue that, in theory, over-shifting can occur in markets with a high degree of unobserved tax evasion. Analogously, subsidy over-shifting can also happen when companies are able to substantially manipulate or exaggerate the variables that determine the total subsidy so that they receive higher payments than the official subsidy amount observed by the econometrician. While we argue in this section that subsidy manipulation is nearly impossible in the context of the CSI rebate,²⁶ we begin by discussing how it could theoretically explain pass-through that exceeds unity.

We consider the case of perfect competition and a per-unit tax t (or a per-unit subsidy s) that is remitted by suppliers. The standard statutory incidence irrelevance result states that a tax levied on the demand side would leave pass-through and incidence unaffected. However, Kopczuk et al. (2016) show that allowing for differences in the ability to evade taxes between consumers and firms alters this well-known result. Pass-through then depends on remittance responsibility and the degree of tax evasion. Differentiating the equilibrium condition D(p) = S(p - t) with respect to the tax rate yields the following pass-through expression for consumers:

$$\frac{dp}{dt} = \frac{\varepsilon_S}{\varepsilon_S + \varepsilon_D} - \frac{\varepsilon_N}{\varepsilon_S + \varepsilon_D} \frac{E[e|t]}{q},\tag{10}$$

where q is total output, e is the total amount of tax evasion, ε_N is the price elasticity of the number of firms in equilibrium, and other variables are as previously defined.

We refer to Kopczuk, Marion, Muehlegger and Slemrod (2013) for the derivation but demonstrate here that their result implies the possibility of over-shifting. First, note that if there is no tax evasion (e = 0), the pass-through expression is identical to Equation 1. Next, when there is evasion (e > 0), there is a negative adjustment term applied to the standard pass-through expression. In other words, the tax-inclusive consumer price increases by less when firms (or consumers) can evade taxes. This is intuitive: firms and consumers together remit fewer taxes to the government than the official tax rate would suggest. This mitigates price changes. As econometricians, we interpret this as lower pass-through to consumers, even though firms end up paying lower taxes, too.²⁷

The case of unobserved subsidy manipulation differs slightly. First, $\frac{dp}{ds} = -\frac{dp}{dt}$. Second, subsidy exaggeration in Kopczuk et al. (2016)'s setting goes in the opposite direction from tax evasion e (i.e., e is negative, as exaggeration is "negative evasion"): higher subsidies lead to more rents

²⁶Subsidy manipulation (or tax evasion) is conceivable in other markets or with other subsidies. For instance, in the U.S. solar market, there were allegations that the investment tax credit was subject to manipulation. We discuss below that this does not affect our pass-through estimates.

 $^{^{27}}$ Our analysis assumes that the firm has full remittance responsibility. However, if firms or consumers have differential abilities to evade taxes, the evasion effect on pass-through is larger when the remittance responsibility of the tax is shifted towards the side of the market with better abilities to evade. See Kopczuk et al. (2016) for a full treatment of this intuitive result.

from manipulation, part of which benefits consumers in the form of lower subsidy-inclusive prices. Taken together, the effect of subsidy manipulation on $\frac{dp}{ds}$ is negative—the same official subsidy leads to a larger decrease in subsidy-inclusive consumer prices in the presence of manipulation. In our regression framework, we would interpret that as higher pass-through. Intuitively, there is more subsidy money to be distributed between consumer and firm, which benefits consumers ("higher pass-through") even if the firm captures most of the manipulated subsidy increase.

Importantly, Equation 10 does not prevent the pass-through coefficient of the manipulated subsidy from exceeding 100%. In fact, if subsidy pass-through was close to 100% in a market without manipulation, even a modest amount of subsidy exaggeration could lead to over-shifting. Note that this issue only arises if the actual (manipulated) subsidy received is unobserved and the econometrician only knows the statutory subsidy amount. If firms manipulate subsidies but we observe what they actually receive, the usual pass-through results from Section 2 apply and the subsidy exaggeration cannot explain over-shifting. We thus conclude that subsidy manipulation, if unobserved, increases estimated pass-through coefficients and can move them above 100% under special circumstances.

Although this sheds light on another potential explanation for over-shifting, the CSI rebate is almost certainly not subject to unobserved subsidy manipulation, ruling out this potential explanation for our over-shifting finding. The rebate amount is not determined based upon reported prices or imputed values but rather by the effective (i.e., location- and system-adjusted) system size. Manipulating such system features, which are transparent and easily verified through inspection, is extremely difficult or even impossible.²⁸

For completeness, we mention that recent stories in the media report that third-party solar leasing and installation firms manipulated a different solar subsidy: the federal investment tax credit (ITC) (Greentech Media 2013). The ITC is 30% of the estimated value of solar systems, which some firms have allegedly inflated in order to reap larger ITCs. This manipulation was only possible for TPO systems, as there is no arm's length transaction price between the installer and the new owner (the leasing department of the same integrated company). For HO systems, the ITC was calculated based on the actual transaction price between the homeowner and the installation company, which is much harder to manipulate. These practices do not affect our estimates as we study the pass-through of CSI (not ITC) subsidies.²⁹

Decreasing Marginal Costs.—Standard short-run analyses assume diminishing returns to inputs, or in other words, increasing marginal costs of production, and thus the supply elasticity $\varepsilon_S > 0$. It follows immediately from Equation 1 that pass-through cannot exceed unity under this assumption in perfectly competitive markets (barring Giffen behavior). Nonetheless, over-shifting theoretically

²⁸Furthermore, such manipulation would have been a very high-risk endeavor considering a proportion of projects were inspected to ensure accurate reporting, and thus the program was administered in a way that safeguarded against such behavior. An official administering the CSI program confirmed this.

²⁹In addition, the value of the CSI rebate is independent of whether or not companies manipulated the ITC. As discussed in Appendix B.2, an extra dollar of CSI rebates reduces the value of the total ITC received by \$0.30, regardless of whether the ITC amount was overstated or not.

can occur if $\varepsilon_S < 0$. However, this could only happen in industries with such strong returns to scale that the marginal cost function is decreasing in the short run. Also note that increasing returns to inputs often leads to an unstable equilibrium that requires government intervention (e.g., natural monopoly).

Decreasing marginal costs are highly uncommon in general and are certainly not observed in the California solar market.³⁰ Consideration of the TPO market's cost structure strongly suggests non-declining short-run marginal costs. The majority of the solar system cost is driven by "soft" costs such as labor, inventory and marketing. The TPO market is already characterized by a few dominant firms that employ sophisticated methods to take advantage of their scale in reducing such costs. Although one can imagine longer-run scale advantages from more efficient installation procedures or customer acquisition for small firms, it is difficult to imagine how increasing returns to labor and other installation cost inputs would have occurred in the short run for mature firms.

Nominal Pricing Rigidities.—Conlon and Rao (2016) demonstrate that nominal rigidities in prices can rationalize pass-through over-shifting regardless of the shape of the underlying demand curve. While price changes that occur in coarse increments exist in specific contexts, such as in their empirical setting of distilled spirits markets, this is not the case in many markets and certainly not for solar systems.

6 Demand Curvature and Over-Shifting

Our empirical estimates in Section 4 show that the pass-through rate of solar subsidies in the residential sector has been high, with pass-through for HO around 80-90% and substantially above 100% (around 160-180%) for TPO. In Section 2, we discuss that such over-shifting is theoretically possible under imperfect competition when demand is sufficiently convex and indeed observed in various markets.

We now connect the theory of over-shifting—as elegantly laid out by Weyl and Fabinger (2013) with our solar market data. We aim to test if our data support a demand specification that is consistent with the over-shifting observed in the California solar market. In other words, we need to investigate if demand for residential solar systems is sufficiently convex to explain pass-through above unity in an imperfectly competitive market. To do this, we construct an empirical test of the over-shifting theory. While this may seem to be a natural subsequent inquiry in an empirical paper that finds more-than-complete pass-through, earlier papers that estimate pass-through rates have not explicitly connected the theory of pass-through under imperfect competition with an empirical test of demand convexity.

We begin by estimating demand for solar systems in the HO and TPO markets separately. In doing so, it is of crucial importance to specify a flexible enough demand function that allows for

 $^{^{30}}$ The only empirical evidence of declining marginal costs that we are aware of is Bower (1964), who studies brick production and attributes the peculiar short-run cost behavior to limited flexibility in some production inputs and the presence of labor indivisibilities, which both contribute to increasing returns to variable inputs.

concave, convex or very convex demand. We therefore take the approach of estimating quadratic demand specifications for HO and TPO systems, computing the range of prices (if any) over which Seade (1985) and Weyl and Fabinger (2013) would predict over-shifting, both for HO and TPO, and testing whether our pass-through estimates are consistent with these price ranges.

As it turns out, this analysis is complicated by the fact that the relevant convexity parameter ε_{ms} from the pass-through theory (defined below Equation 2)—and therefore the range of prices over which one would expect over-shifting in a market characterized by imperfect competition is sensitive to the parameters of a flexibly estimated demand specification. Therefore, the main contribution of this exercise is not to provide precise price ranges over which over-shifting occurs in the solar markets studied here but rather to illustrate how the theory of over-shifting can be empirically tested with a standard demand estimation. We provide—to the best of our knowledge—the first empirical test of consistency between over-shifting and demand curvature. As such, we show that empiricists can directly test pass-through theory to lend additional credibility to empirical estimates of pass-through rates that exceed 100%, by taking demand curvature seriously.

We cannot emphasize enough, however, that our demand estimates are noisy, so our conclusions about the exact price range over which we predict over-shifting under imperfect competition need to remain modest. We consider the analysis below to be a compromise between a full-fledged test based on a complete and precise demand estimation and an extensive numerical example. Nonetheless, the exercise illustrates the mechanics of how one could implement such a test given the availability of sufficiently rich data.

6.1 Demand Estimation

6.1.1 Econometric Framework

We estimate a demand equation that flexibly allows for different degrees of convexity or concavity. We choose the simplest form: demand for solar systems as a quadratic function of their prices. The coefficient on the squared price term directly measures convexity. The usual simultaneity bias justifies an instrumental variables estimator. We estimate the following equation by 2SLS with data aggregated at the zip code by year level:

$$q_{it} = \beta_1 p_{it} + \beta_2 p_{it}^2 + \mathbf{X}_{it} \theta + \delta_j + \tau_t + \varepsilon_{it}, \tag{11}$$

where *i* indicates zip code and *t* denotes year. The dependent variable q_{it} is the installation rate defined as the number of residential solar systems installed in a particular zip code and year per 1,000 inhabitants. We normalize by population given the vast differences in population across zip codes in California. On the right-hand side, p_{it} is the post-incentive price per watt, δ_j are county fixed effects, τ_t are year fixed effects, and ε_{it} is an error term. \mathbf{X}_{it} includes the same demographic controls that we use in the pass-through regressions in Section 4 as well as electricity rates.

Although our model includes year fixed effects, electricity rates—which affect demand for solar because higher electricity prices increase electricity bill savings realized from solar adoption—change

within year. Electricity prices in California follow a tiered rate structure, where electricity rates increase with household consumption. We follow Hughes and Podolefsky (2015) and include each IOU's rates for the three highest tiers.

We identify our demand parameters based on zip code and time variation in the solar installation rate and price after controlling for observables and instrumenting for the price. We instrument for p_{it} and p_{it}^2 using a set of supply shifters. We follow Gillingham and Tsvetanov (2016) in using the rebate and its square (as defined and used in the pass-through regressions from Section 4) as well as the county-level electrician/wiring wage rate and its square. The latter is a proxy for solar installer wages.

Both CSI rebates and wages are credible instruments since they plausibly affect demand only through their effect on the price of the solar system. Any instrumental variables estimator assumes an exclusion restriction—ours is that any omitted demand shifters that end up in the error term are uncorrelated with our instruments (rebates and wages). The inclusion of year and county fixed effects flexibly account for time trends in installation rates that are common across zip codes, as well as time-invariant differences across zip codes. These absorb some complications from swings in macroeconomic conditions during our sample period. However, there might be omitted demand shifters, such as changes in tastes for the visual aspects of solar panels or preferences towards being less reliant on the incumbent utility company, that exhibit different trends in different zip codes. Such omitted variables could introduce bias insofar as they correlate with our instruments. Through the exclusion restriction, we maintain the assumption that the impact of such variables is negligible.

6.1.2 Data

The underlying dataset is the same as in the pass-through analysis (see Section 4 for details), except that we add to each installation the corresponding tiered electricity rates (based on location and date at which the household applied for the CSI rebate) and county-level data on electricity/wiring wages from the U.S. Bureau of Labor Statistics. Additionally, we keep all TPO installations, not just those whose contracts have been transcribed. We then aggregate the data to the zip code by year level, separately for HO and TPO systems, and interpolate missing data with county-level averages. This interpolation is necessary for zip code-year observations with zero installations. The final dataset contains data on installations rates, contract types, prices and control variables for 1,958 zip codes for each of the years 2010-2013. See Appendix B.1 for more details.

6.1.3 Results

Table 6 shows the results of the demand estimation. We provide OLS results in columns 1 and 2 and IV estimates in columns 3 and 4. Across all specifications, we find that demand is convex, as indicated by the positive coefficients on the squared price term. The IV estimates pass the weak instruments test, but they are imprecisely estimated, not statistically significant, and they differ from the OLS estimates. Still, IV is the theoretically correct way to estimate demand. While

acknowledging the limitations from large standard errors, we continue to illustrate the implications of our estimated demand parameters for over-shifting.

| | (1) | (2) | (3) | (4) |
|----------------------------|-----------|---------|---------|-----------|
| | 0 | LS | Ι | V |
| | HO | TPO | HO | TPO |
| _ | | | | |
| Price | -0.49 | -0.259* | -1.754 | -3.166 |
| | (0.311) | (0.140) | (1.873) | (2.420) |
| $Price^2$ | 0.048* | 0.039** | 0.208 | 0.460 |
| | (0.028) | (0.018) | (0.235) | (0.321) |
| Mean of dependent variable | 0.495 | 0.534 | 0.495 | 0.534 |
| First stage F-statistic | | | 10.610 | 17.303 |
| p-value | | | 0.000 | 0.000 |
| Controls | х | х | х | х |
| County FE | x | х | х | х |
| Year FE | x | х | х | х |
| Number of observations | $5,\!384$ | 5,384 | 5,384 | $5,\!384$ |

Table 6: Demand Estimates for HO vs. TPO Systems

Notes: Dependent variable is the solar system installation rate. Observations are at the zip code by year level. Data cover systems installed in California for consumers who applied for the CSI rebate during the period 2010-Q2 2013. Controls includes the same demographics that we use in Table 2, as well as tiered electricity rates. A 7% discount rate is assumed for the net present cost and MACRS calculations. IV estimates in columns 3 and 4 instrument for (squared) price using the (squared) CSI rebate and the (squared) county-level electrician/wiring wage rate. Standard errors clustered by zip code. Asterisks denote *p < 0.10, **p < 0.05, ***p < 0.01.

When translating the parameter estimates from the IV specifications in Table 6 to price elasticities, we find that, at the average price in our sample of \$3.70 per watt, the demand elasticity is -0.85 for HO and -0.42 for TPO.³¹ Demand becomes more elastic as prices decrease. The relative inelasticity of demand for TPO versus HO systems suggests one reason why pass-through rates are higher for TPO, yet this alone cannot explain over-shifting.

6.2 Implications for Over-Shifting

Theory predicts that, under monopoly and many other forms of imperfect competition, over-shifting occurs when demand is sufficiently convex, i.e. $1/\varepsilon_{ms} < 0$, as summarized by Equation 5. Having estimated separate demand functions for HO and TPO consumers, we now calculate $1/\varepsilon_{ms}$ using our estimated demand coefficients along different points of these demand curves (see Appendix C.3 for details).

The 1st to 99th percentile range for system prices in our sample is approximately two to six dollars per watt, with an average price of \$3.70 per watt that decreases over time. When we evaluate our IV demand estimates from columns 3 and 4 in Table 6 above, we find that $1/\varepsilon_{ms} < 0$

³¹Our estimates are generally in the same range as others in the literature. Gillingham and Tsvetanov (2016) find a price elasticity of demand for solar PV systems of -1.76 in Connecticut. However, using California data, Hughes and Podolefsky (2015) estimate a "rebate elasticity" of approximately -1.2, which is most usefully comparable to our estimate for HO systems. No other studies have estimated elasticities for the TPO market.

for prices above \$3.04 per watt for HO systems. For TPO systems, $1/\varepsilon_{ms} < 0$ if the price per watt exceeds \$2.63. Hence, our demand equations are consistent with two observations from our empirically estimated pass-through rates. First, the estimated curvature of demand for both HO and TPO systems is consistent with over-shifting occurring over at least some range of demand, and this range covers reasonable prices for this market and time period. This suggests that the solar market indeed has the characteristics of a market in which market power could lead to overshifting. Second, the price range for which theory predicts over-shifting is slightly larger for TPO systems, though the difference is not statistically significant. This connects with our pass-through estimates, which indicate over-shifting on average for TPO but not for HO across the full sample.

As discussed above, we include this analysis to demonstrate how flexibly estimating demand can help provide further evidence to support empirical estimates of over-shifting. While the curvature of demand in the residential solar sector appears consistent with the possibility of over-shifting, and perhaps indeed more so for TPO than for HO systems, we also remind the reader that our demand equations are imprecisely estimated and the convexity ranges are sensitive to demand parameters. Nonetheless, this procedure can be applied more broadly to provide supporting evidence for empirical findings of over-shifting, which can in turn be used to argue for the presence of market power if alternative explanations can be convincingly ruled out.

7 Conclusion

Pass-through is an important tool of economic analysis as it can reveal important characteristics about supply, demand, or market power. In this paper, we estimate pass-through of solar subsidies to consumers in an important empirical setting: the market for solar systems in California under the California Solar Initiative, the largest state solar rebate program to date in the United States. We allow pass-through to differ between HO and TPO markets. We find that pass-through is remarkably high and differs substantially for buyers versus lessees. Pass-through to consumers who purchase their solar panels is about 86 cents for every dollar increase in subsidies. For leases, a \$1 increase in subsidies translates to a decrease in solar system prices of \$1.65. This more-thancomplete pass-through is surprising and does not support popular claims that solar companies appropriate most of the subsidies.

The substantial over-shifting in the leasing market can be explained by imperfect competition combined with "sufficiently convex" demand, but there exist other conditions—including but not limited to Giffen behavior, decreasing marginal costs, and unobserved subsidy manipulation—under which over-shifting can occur. We formalize pass-through over-shifting as an under-utilized test for market power by outlining and ruling out these alternative explanations. We conclude that, in the setting of the California solar market, over-shifting can only be rationalized by imperfect competition and sufficiently convex demand. We reinforce this conclusion with an empirical test of demand curvature for solar systems, which indeed suggests sufficiently convex demand.

This paper is the first to estimate pass-through of green energy subsidies in a third-party market

and to contrast pass-through for buyers and lessees of (virtually) the same product. Our results shed light on how the benefits of such subsidies accrue across different types of consumers and firms, which should be of interest to policy makers. The substantial difference in pass-through is not only interesting to highlight that HO and TPO systems cannot be treated as a single market for solar panels, but also because it suggests that buy and lease markets could differ in other contexts, such as automobiles, planes, and computers. Consequently, future research could focus on how tax incidence differs across the buy and lease segments of such markets.

Perhaps most importantly, we argue that estimating pass-through and finding that it over-shifts can serve as a powerful diagnostic for detecting market power that can be applied beyond the solar market. Such an analysis is attractive as the estimation is usually straightforward and imposes only limited data and computational demands. Competition authorities therefore should be particularly interested in industries characterized by over-shifting, as this is often a strong signal that they are at risk of imperfect competition and may require further investigation. Of course, pass-through over-shifting is a relatively unusual finding, and its absence does not imply that the market is perfectly competitive.

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A Appendix: Theory and Proofs – For Online Publication

A.1 Pass-Through in the Presence of Market Power

We provide the equation for pass-through under monopoly in Equation 2 of the main text. Drawing directly from Weyl and Fabinger (2013), we derive this equation here by considering the monopolist's optimization problem and solving for the pass-through rate ρ , or the rate at which the price, p, changes with marginal cost, mc. The monopolist's revenues are p(q)q with marginal revenue mr(q) = p(q) + p'(q)q and marginal cost mc(q) = c'(q). The monopolist maximizes profits by choosing quantity such that mr(q) = mc(q) + t, where t is a per-unit tax on producers. Thus,

$$mr'\frac{dq}{dt} = mc'\frac{dq}{dt} + 1 \Rightarrow \frac{dq}{dt} = \frac{1}{mr' - mc'}$$

$$\Rightarrow \rho = \frac{dp}{dt} = p'\frac{dq}{dt} = \frac{p'}{mr' - mc'}.$$
(A.1)

Marginal revenue, mr = p + p'q, is made up of two terms, the price p and the negative of the marginal consumer surplus ms = -p'q, which is what consumers earn when quantity expands. As such, we can write

$$\rho = \frac{1}{\frac{p'-ms'}{p'} - \frac{mc'}{p'}} = \frac{1}{1 + \frac{\varepsilon_D}{\varepsilon_{ms}} \frac{ms}{p} + \frac{\varepsilon_D}{\varepsilon_S} \frac{mc}{p}},$$
(A.2)

where $\varepsilon_D \equiv -D'p/q$ is the elasticity of demand, $\varepsilon_S \equiv S'p/q$ is elasticity of supply, and the elasticity of the inverse marginal surplus function is $\varepsilon_{ms} = ms/(ms'q)$. We can further simplify the passthrough equation using

$$\frac{ms}{p} = -\frac{p'q}{p} = \frac{1}{\varepsilon_D} \tag{A.3}$$

and Lerner's (1934) rule

$$\frac{p - mc}{p} = \frac{1}{\varepsilon_D} \Rightarrow \frac{mc}{p} = \frac{\varepsilon_D - 1}{\varepsilon_D}$$
(A.4)

to yield

$$\rho = \frac{1}{1 + \frac{\varepsilon_D - 1}{\varepsilon_S} + \frac{1}{\varepsilon_{ms}}}.$$
(A.5)

As discussed in the main text of the paper, there are two key differences between pass-through under perfect and imperfect competition. First, $\varepsilon_D - 1$ has replaced ε_D . Second, more importantly, there is the new term containing the inverse elasticity of marginal surplus, ε_{ms} , which measures the curvature of (the logarithm of) demand. In other words, pass-through under imperfect competition is not just determined by the elasticity of supply and demand but also the curvature of demand.

As Weyl and Fabinger (2013) discuss more extensively, the inverse elasticity of marginal surplus,

 ε_{ms} , measures the curvature of the logarithm of demand. Recall ms = -p'q and $D \equiv D(p)$, so D' = dD/dp = dq/dp, and thus

$$(log D)' = \frac{D'}{D} = \frac{\frac{dq}{dp}}{q} = \frac{1}{\frac{dp}{dq}q} = \frac{1}{p'q} = -\frac{1}{ms}$$
 (A.6)

and

$$(log D)'' = \frac{ms'}{ms^2} \frac{1}{p'} = -\frac{1}{\varepsilon_{ms}} \frac{1}{ms} \left(-\frac{1}{p'q} \right) = -\frac{1}{\varepsilon_{ms}} \frac{1}{ms^2}.$$
(A.7)

Hence, demand is log-concave when $1/\varepsilon_{ms} > 0$ and log-convex when $1/\varepsilon_{ms} < 0$. Another threshold of interest is that $1/\varepsilon_{ms} > 1$ for concave demand and $1/\varepsilon_{ms} < 1$ for convex demand. This is because the inverse elasticity of marginal surplus is

$$\frac{1}{\varepsilon_{ms}} = \frac{ms'q}{ms} = \frac{(p''q + p')q}{p'q} = 1 + \frac{p''q}{p'}$$
(A.8)

and given that q > 0 > p', the second term p''q/p' is positive if p'' < 0 and $1/\varepsilon_{ms} > 1$, and vice versa.

One can follow similar steps to derive pass-through for the more general case of symmetric, imperfect competition, which Weyl and Fabinger (2013) show is

$$\rho = \frac{1}{1 + \frac{\theta}{\varepsilon_{\theta}} + \frac{\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}},\tag{A.9}$$

where θ is a conduct parameter between zero for perfect competition and one for a pure monopoly. Analogous to the case of the monopoly with cnostant marginal costs (infinite ε_S), pass-through exceeds unity if and only if ε_{ms} is negative since $1/\varepsilon_{\theta} = 0$ for many standard models of imperfect competition, such as Cournot.

A.2 Second Order and Stability Conditions

We primarily focus on the threshold for pass-through over-shifting to occur. For completeness, we note that one may also wish to check the range of ε_{ms} values against the second order and stability conditions for the firm's profit maximization problem to ensure consistency with stable symmetric market equilibrium. The second order condition states that the second derivative of the profit function is non-positive. Stability implies that equilibrium is restored when disturbing an initial equilibrium by changing each firm's output by any specified amount δ .

Seade (1985) derives these conditions. In our notation, the second order condition under symmetry can be written as

$$\varepsilon_{ms} < \frac{1}{1 - 2n},\tag{A.10}$$

where n is the number of firms in the market. The stability condition that is necessary and sufficient

under symmetry can be written as

$$\varepsilon_{ms} < -\frac{1}{n}.\tag{A.11}$$

This implies that a stable equilibrium requires stricter conditions than $\varepsilon_{ms} < 0$ on the range of prices over which over-shifting occurs.

B Appendix: Data – For Online Publication

B.1 Additional Details on Data Preparation

B.1.1 Data for the Pass-Through Regressions

The CSI dataset that we start with is the public "working dataset" file posted on the CSI website on June 24, 2015.³² We took a few other steps to prepare the data in addition to what we describe in Section 3. First, through the National Renewable Energy Laboratory (NREL), we obtained a non-disclosure agreement with the California Public Utilities Commission to gain access to and transcribe detailed terms from a proprietary dataset of residential third-party solar contracts in California. Obtaining usable price data from these required our manual transcription because they lacked consistency across contract type and company, and they were often hand-written. As such, we stratified the data by quarter and drew a random sample of 200 observations per quarter of all residential TPO projects with a CSI completion date. Not all contracts that we sampled contained enough data to construct a net present cost (NPC), leaving us with 1,346 contracts in total with usable data.

We impose a number of sample selection rules on the full dataset. We drop a small number of observations that are most likely data errors. These include two systems with prices above \$20/watt and seven systems with prices below \$0.50/watt. Next, we limit the data to installations with status listed as "installed" or "pending" because if "cancelled" the recorded contract terms likely do not reflect market conditions. We also drop 13 systems for which the listed incentive amount exceeds the total reported system cost, which is infeasible and thus data entry error.

We keep only residential systems and those who participate in the Expected Performance Based Buydown (EPBB) program, which was the upfront lump-sum rebate option offered by CSI. While residential customers could use a Performance Based Incentive (PBI) instead, more than 99% of residential consumers opted for EPBB. We also drop observations filed under the Multifamily Affordable Solar Housing (MASH) program as decision-making for multi-family housing is fundamentally different from individual households. Another non-representative class of contracts that we drop is those with "GRID Alternatives", a nonprofit that brings together community partners, volunteers, and installers to implement projects for low-income families.

We restrict our dataset to systems up to 10 kilowatts, as larger systems are highly unlikely to have a residential-only purpose. Almost all residential solar electric systems require between 50

³²The CSI data are available online at https://www.californiasolarstatistics.ca.gov/data_downloads/

square feet and 1,000 square feet, and a general rule that is often applied is that 100 square feet of solar panels will generate 1 kilowatt of electricity (Hois 2016). For systems above 10 kilowatts, there is a high risk of data errors and confusion with small commercial systems, which are outside the scope of the market we are interested in studying.

We extend the dataset by merging in demographics at the census tract level using demographics from the American Community Survey. For that purpose, researchers at NREL geocoded the CSI data with latitudes and longitudes from address locations. We merged this with the post-incentive price data as well as the CSI data.

Finally, we end our sample at the end of June 2013. At that time, the CSI program was nearly exhausted. While Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E) territories still provided CSI rebates at the lowest level, Pacific Gas & Electric (PG&E) ran out of CSI funding at the end of April 2013.

B.1.2 Data for the Demand Regressions

The dataset we use for the demand regressions is similar to that for the pass-through regressions, but we modify it in a number of important ways.

First, we need to include *all* TPO installations, not just those whose contracts we transcribed. Second, as the CSI applied to the three IOUs but not municipal utilities, we need to treat zip codes with partial IOU-coverage carefully. To that end, we obtained information on all California zip codes serviced by one of the three IOUs as well as zip codes covered by California's municipal and other utilities, which were not eligible for the CSI.³³ We then drop zip codes that are not serviced by one of the three IOUs or serviced in part by an IOU and in part by a municipal utility.

Finally, we applied a few more detailed sample selection rules. We manually went through all zip codes and dropped 13 zip codes that are not flagged as partially outside IOU territory, but a detailed service area map from the California Energy Commission disagrees.³⁴ We also drop 133 zip codes with zero population; these are business districts or P.O. boxes.

Third, we aggregate the data to the zip code by year level. We employ the following procedure to calculate zip code by year level prices and control variables. When such variables are missing for a particular observation (most commonly for zip code-year observations with zero installations), we take the county by year average, separately for HO vs. TPO systems. If the county by year aggregate is still missing (highly unlikely, but possible for some variables), we take the populationweighted average over neighboring counties. In this aggregation process, we sum the installations by year for each zip code and contract type. Since we have a limited time series but only partial coverage of the year 2013, we pro-rate the installation rate for 2013 using the end date for each

³³For PG&E, see https://www.pge.com/tariffs/tm2/pdf/ELEC_MAPS_Service_Area_Map.pdfandwww.pge.com/tariffs/RESZIPS.XLS. For SCE, https://www.sce.com/wps/wcm/connect/690b717f-8c57-469b-a87a-ad02decbf9d0/MasterZipCode_DiscBulbs.pdf?MOD=AJPERES. For SDG&E, see https://energydata.sdge.com/. For LADWP, see https://data.lacity.org/A-Livable-and-Sustainable-City/LADWP-Power-use-by-zipcode-GOVSTAT-/a752-uami/data. For other non-IOU zip codes, see https://catalog.data.gov/dataset/u-s-electric-utility-companies-and-rates-look-up-by-zipcode-feb-2011-57a7c.

³⁴http://www.energy.ca.gov/maps/serviceareas/electric_service_areas.html

utility (discussed above) and the fraction of systems that were installed in the sample period over the period 2010-2012 (44.34% for SCE, 42.61% for SDG&E, and 26.42% for PG&E).

B.2 Adjusting the CSI Rebates for ITC and MACRS Subsidies

This section details the method we employed to adjust the CSI rebate to account for its interaction with pre-existing federal incentives, as explained in Section 4.1. Federal incentives available throughout the sample period include the investment tax credit (ITC) for both HO and TPO systems, and the Modified Accelerated Cost Recovery System (MACRS) benefits for TPO systems only. We begin by examining the case of HO systems. Recall that the post-incentive price for HO consumers is the reported total cost minus incentives, such that

$$p_{HO,i} = TC_{HO,i} - CSI_{HO,i} - ITC_{HO,i}, \tag{B.1}$$

where $p_{HO,i}$ is the post-incentive price for HO consumer *i*, $TC_{HO,i}$ is the total reported cost in the CSI database, $CSI_{HO,i}$ is the total CSI rebate amount awarded, and $ITC_{HO,i}$ is the implied federal ITC benefit. We do not observe the ITC, so we calculate this assuming that it is fully monetized for all cases. For HO consumers, the CSI rebate is considered a price reduction for tax credit purposes. Thus, the 30% tax credit applies to the after-rebate net price paid by the customer:

$$ITC_{HO,i} = 0.3 * (TC_{HO,i} - CSI_{HO,i}).$$
(B.2)

The pass-through of the ITC and CSI incentives cannot be separately identified in our regression model because they are linear functions of each other, however we must account for the way in which they interact. As implied by Equation B.2, a one-dollar increase in the CSI rebate is effectively a 70 cent increase in total subsidies because the CSI mechanically decreases the value of the ITC by 30 cents. We account for this interaction by adjusting the CSI rebate amount that is used in our pass-through regressions. To do that, note that we can re-write Equation B.1 such that

$$p_{HO,i} = 0.7 * (TC_{HO,i} - CSI_{HO,i}).$$
(B.3)

However, if we did not adjust our measure of the CSI subsidy, our regression would estimate

$$p_i \sim \alpha + \beta CSI_i + \varepsilon_i, \tag{B.4}$$

where a one-dollar increase in the CSI subsidy would be interpreted as a one-dollar increase in the total subsidy received. As the actual one-dollar increase in the CSI is worth only 70 cents from the consumer's and installer's perspectives, we multiply the CSI subsidies by a correction factor of 0.7, as we want to interpret our pass-through coefficient β as the impact on prices of a full one-dollar subsidy increase.

Adjusting for federal incentives for TPO systems differs somewhat from the HO adjustment for two reasons: the ITC is calculated in a slightly different way, and TPO systems also benefit from MACRS. The post-incentive price that we construct for TPO systems is a net present cost calculation that embeds all incentives (since contract terms are subsidy-inclusive). As such, we do not need to explicitly net out the ITC and MACRS from a gross cost measure (as we do for HO consumers). However, we note that for TPO consumers

$$p_{TPO,i} \equiv NPC_{TPO,i} = U_i + \sum_{y=1}^{t} \frac{payment_{iy}}{(1+d)^t},$$
(B.5)

where $p_{TPO,i}$ is the post-incentive price of system *i*, or the net present cost of the contract to the customer as described by Equation 7, which embeds the ITC and MACRS. As before, we need to account for these other incentives in our pass-through regressions as they interact with the CSI rebate. First consider the ITC for TPO consumers. The CSI rebate is not a price reduction for tax credit purposes as it is for HO consumers. Instead, the federal ITC received by third parties is based on gross installed cost: $ITC_{TPO,i} = 0.3 * TC_{TPO,i}$. The ITC is thus unaffected by the CSI as the basis for the 30% credit is not reduced by the CSI rebate amount. However, the IRS considers the CSI rebate to be earned income and therefore subject to corporate taxes. Hence, the effective CSI subsidy is $(1 - t_c)CSI$, where t_c is the corporate tax rate. Hence, we need to multiply the CSI subsidies by $(1 - t_c)$ in the TPO case in order to interpret our pass-through coefficient as the impact of a full dollar increase in the rebate. We do not observe the effective marginal tax rate of each installer in our sample, but following Borenstein (2017), we assume it is 30%—close but somewhat lower than the 35% rate for large companies. Using 35% would scale up our ITC pass-through estimates and make the estimated difference between HO and TPO pass-through even more pronounced.

The second federal subsidy to take into account is MACRS. Over our entire sample period, residential solar PV systems were eligible for 5-year accelerated depreciation as well as an especially high "bonus" depreciation in the first year. For systems placed into service after September 8, 2010 and before January 1, 2012, the first-year bonus depreciation rate was 100%; it was 50% during the other periods in our sample. Under 50% first-year bonus depreciation, the depreciation schedule was (50% bonus + 10% MACRS =) 60%, 16%, 9.6%, 5.76%, 5.76% and 2.88% for years one through six, respectively. Under 100% first-year bonus depreciation, the system was fully depreciated for tax purposes in year one.

Our goal is to calculate a MACRS "adjustment factor" based upon the structure of the MACRS program assuming a one-dollar increase in the CSI rebate. We use Borenstein (2017)'s assumptions. Again, we want to interpret a one-dollar increase in the CSI subsidy as a one-dollar increase in total subsidy received. The reasoning is similar to that for the ITC adjustment in the case of HO: there is a reduction in the present value of the MACRS benefit following a one-dollar increase in CSI because firms were able to depreciate 85% of the system cost *after state rebates*. In other words, the allowable depreciable basis is equal to 0.85 * (TC - CSI). The net present value of the TPO systems is

$$MACRS_{factor} = \sum_{y=1}^{6} \left(\frac{m_y}{(1+r)^y} * t_c * D \right),$$
(B.6)

where m_y is the MACRS recovery rate in year y, r is the firm's discount rate, and t_c is the firm's marginal corporate tax rate (which we assume to be 30%, following Borenstein (2017)). D is the allowable depreciable basis, which is equal to 0.85 for solar PV systems.

We calculate real adjustment factors for a range of nominal discount rate assumptions that align with our NPC calculations (2% to 12%). Furthermore, we calculate different sets of adjustment factors based on when the program allowed for 50% and 100% bonus depreciation. We assume that all third parties took advantage of the MACRS program. We thus determine if systems qualified for 50% or 100% bonus deprecation based upon installation date, since eligibility was determined based on the date the system went into service. This date is not included in the CSI database, so we matched the CSI data to the publicly available NEM interconnection dataset. $MACRS_{factor}$ ranges from 0.21 to 0.25 depending on the discount rate and the type of bonus depreciation.

Finally, we adjust the CSI rebates for ITC, corporate taxes, and MACRS benefits for our pass-through regressions such that

$$AdjustedCSI_{HO,i} = 0.7 * CSI_{HO,i} \tag{B.7}$$

and

$$AdjustedCSI_{TPO,i} = 0.7 * CSI_{TPO,i} * (1 - MACRS_{factor}).$$
(B.8)

C Appendix: Additional Figures and Tables – For Online Publication

C.1 Additional Theory Figures

In Figure 1 of the main text we show how over-shifting occurs in the presence of market power when demand is log-convex. Figure C.1 demonstrates two related cases where pass-through cannot exceed unity to further illustrate why both sufficiently convex demand and market power are needed to explain over-shifting. Panel A illustrates how pass-through falls between 0 and 100% under perfect competition but with convex demand. Perfectly vertical marginal costs would imply 0% pass-through and flat marginal costs would imply 100% pass-through. Panel B shows how pass-through is exactly 50% for the case of monopoly but with linear demand and constant marginal costs.







(a) Pass-Through under Perfect Competition and Constant Elasticity Demand

(b) Pass-Through for a Monopolist with Linear Demand and Constant Marginal Costs

Note: Figure shows the price effect of a subsidy s on the price p under perfect competition when there is constant elasticity demand and when p is set by a monopolist under linear demand. MC refers to marginal cost, D to demand, and MR to marginal revenue. The constant elasticity parameter in panel A is $\epsilon = -0.5$.

C.2 Additional Robustness Checks for the Pass-Through Estimates

Figure C.2 shows the total daily installations in each of the three IOU territories for our sample period 2010Q1-2013Q2.³⁵ The figures demonstrate some amount of bunching of applications just before the rebate drop dates. This is consistent with the findings in Hughes and Podolefsky (2015).³⁶

This bunching reflects a certain degree of strategic timing behavior on part of consumers and installers, as they attempted to apply for the CSI rebate before an anticipated rebate level drop. Although drop dates could not be perfectly foreseen as they were triggered by reaching a threshold of cumulative installed capacity within each IOU, the CSI announced on a public website how many CSI megawatts (MW) worth of rebates remained in the current incentive step level. This web-based *CSI Trigger Tracker* allowed users to anticipate when the rebates were going to drop to the next level by comparing "MW Under Review" with "MW Remaining". The rebate level is determined at the time of the reservation, not the time of project completion, so it was possible to strategically submit reservations as each IOU approached step capacity targets.

The possibility on behalf of economic agents to influence on which side of a threshold they end up complicates the interpretation of a regression discontinuity estimation. A comparison of prices just before and after rebate level changes will yield a biased estimate of subsidy pass-through if

³⁵Note that daily "installations" are actually "rebate reservations", since the dates refer to the day when rebate reservations were filed as opposed to when installations were completed.

³⁶CSI residential rebates in the SDG&E region were briefly suspended after January 31st, 2013, but it became clear soon afterwards that residential rebates would continue at the same rate per watt as \$5 million from the commercial solar project budget was shifted to residential installations (Center for Sustainable Energy 2014). Around January 31st, however, some consumers may have thought the CSI rebates had run out while in fact they had not. We therefore show this date as a dotted vertical line in Figure C.2, panel B.

Figure C.2: Total Installations per Day for (a) SCE, (b) SDG&E and (c) PG&E.



(c) Pacific Gas and Electric

Note: The dotted vertical line for SDG&E on January 31^{st} , 2013 indicates a temporary rebate suspension but not an actual rebate drop.

consumers who strategically submit reservation requests differ systematically from those who do not. For instance, consumers who act strategically might be more price-elastic or better informed. In Section 4, we therefore opt for a flexible panel data estimation that estimates the impact of solar subsidies on prices over a longer time horizon, while confirming that "bunching periods" do not affect our main results (Section 4.3).

Table C.1 assesses to what extent our estimates are affected by bunching. We report results from specifications that omit observations within a symmetric window of 4 weeks, 8 weeks, and 12 weeks around the rebate level drop dates in each IOU. Pass-through estimates for HO systems are almost identical to our main estimate in Table 2 (83-84% vs. 86%); the estimates for TPO systems are somewhat higher (170-194% vs. 165%).

| | 4 Weeks | 8 Weeks | 12 Weeks |
|-------------------------------------|-----------|-----------|-----------|
| Incentive | -0.836*** | -0.826*** | -0.840*** |
| | (0.066) | (0.074) | (0.074) |
| Incentive * $1[system = TPO]$ | -0.871*** | -1.118*** | -0.989*** |
| | (0.225) | (0.268) | (0.266) |
| 1[system = TPO] | -0.187 | 0.106 | 0.065 |
| | (0.191) | (0.236) | (0.257) |
| Controls | x | x | x |
| Utility FE | х | х | х |
| Manufacturer FE | х | х | х |
| Module FE | х | х | х |
| County FE | х | х | х |
| Installer FE | х | х | х |
| Quadratic contract type time trends | х | х | х |
| Number of observations | 29,306 | 25,275 | 22,698 |

 Table C.1: Omitting Observations Around Rebate Drops

Notes: Dependent variable is the post-incentive system price per watt. Data cover systems installed in California for consumers who applied for the CSI rebate during the period 2010-Q2 2013. Observations are dropped from a symmetric window of 4, 8 or 12 weeks around rebate drops. Controls include system size, squared system size, a dummy if there is more than one inverter, and census tract level demographics. A 7% discount rate is assumed for the net present cost and MACRS calculations. Standard errors clustered by zip code. Asterisks denote *p < 0.10, **p < 0.05, ***p < 0.01.

C.3 Additional Robustness Checks for the Demand Estimates

C.3.1 Robustness Checks

Table C.2 shows how the demand parameters vary with two important alternative sample selection or variable construction rules. First, we compute the solar installation rate by dividing installations by the number of people who live in houses they own (using information on owner-occupied housing from the census) instead of total population. Renters are unlikely to install solar systems as they do not always capture the full benefits because of limited housing tenure, their apartments or houses are typically less suitable for solar panels, and they need to get property owner approval. Relatedly, homeowners who lease their properties to others may be unlikely to install solar panels when they do not expect to benefit from the electricity bill savings through higher rents. Second, we drop zip codes with populations below 100 people, as these might be unrepresentative of typical residential areas. For example, they could be mostly business districts or extremely sparsely populated areas.

| | (1) | (2) | (3) | (4) | | | | |
|--|-----------|----------|-----------|---------|--|--|--|--|
| A. Installation Rate Based on Owner-Population | | | | | | | | |
| | | | | | | | | |
| | Ο | LS | Γ | V | | | | |
| | НО | TPO | НО | TPO | | | | |
| Price | -0.917 | -0.522** | -3.219 | -5.448 | | | | |
| | (0.601) | (0.260) | (3.618) | (4.272) | | | | |
| Price^2 | 0.090* | 0.078** | 0.380 | 0.805 | | | | |
| | (0.053) | (0.034) | (0.455) | (0.566) | | | | |
| Mean of dependent variable | 0.939 | 0.999 | 0.939 | 0.999 | | | | |
| First stage F-statistic | | | 10.610 | 17.303 | | | | |
| p-value | | | 0.000 | 0.000 | | | | |
| Number of observations | $5,\!384$ | 5,384 | $5,\!384$ | 5,384 | | | | |

 Table C.2: Robustness of Demand Estimates

B. Excluding Zip Codes with Less Than 100 Inhabitants

| | OLS | | Γ | V |
|----------------------------|-----------|-----------|---------|-----------|
| - | НО | TPO | НО | TPO |
| Price | -0.261*** | -0.183* | -0.534 | -1.729 |
| | (0.082) | (0.094) | (0.898) | (2.249) |
| Price^2 | 0.026*** | 0.027** | 0.053 | 0.241 |
| | (0.008) | (0.012) | (0.099) | (0.289) |
| Mean of dependent variable | 0.461 | 0.518 | 0.461 | 0.518 |
| First stage F-statistic | | | 9.842 | 15.280 |
| p-value | | | 0.000 | 0.000 |
| Number of observations | $5,\!196$ | $5,\!196$ | 5,196 | $5,\!196$ |
| Controls | х | х | х | х |
| County FE | х | х | х | х |
| Year FE | х | х | х | х |

Notes: Dependent variable is the solar system installation rate, either based on owner-population (Panel A) or based on total population (Panel B). Observations are at the zip code by year level. Data cover systems installed in California for consumers who applied for the CSI rebate during the period 2010-Q2 2013. Controls includes the same demographics that we use in Table 2, as well as tiered electricity rates. A 7% discount rate is assumed for the net present cost and MACRS calculations. IV estimates in columns 3 and 4 instrument for (squared) price using the (squared) CSI rebate and the (squared) county-level electrician/wiring wage rate. Standard errors clustered by zip code. Asterisks denote *p < 0.10, **p < 0.05, ***p < 0.01.

We conclude that the results when adjusting for homeownership are similar to those in the main specification in Table 6. The parameter values are larger in absolute value, but note that the mean of the dependent variable (the installation rate) is about twice as large since we divide by owner-occupied housing population, not total population. The implied elasticities are also similar.

Similarly, dropping small zip codes does not qualitatively affect our results: the estimates are smaller but still indicate substantial convexity.

C.3.2 Calculating Convexity Measures

In order to calculate the convexity parameter ε_{ms} of Equation 2, we need inverse demand and therefore we invert our estimated demand equation. This is straightforward using the quadratic formula and price and squared price parameters estimated in Table 6. We first calibrate the constant by evaluating our estimated demand equations (one for HO and one for TPO) at a fixed price and with all other control variables at their sample means. From this, we obtain a simplified demand expression $q = ap^2 + bp + c$ (with a and b as the estimates from Table 6 and c calibrated as described above). Next, we solve for p(q) using the quadratic formula. We differentiate the resulting expression to obtain p'(q) and p''(q). This allows us to evaluate the criterion given by Equation A.8 along different points at the demand curves, where $1/\varepsilon_{ms} < 0$ indicates over-shifting under the assumptions of the model. The results are discussed in Section 6 of the main paper.