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Seductive subsidies? An analysis of second-degree moral hazard in the context of solar systems

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Abstract

This paper studies how subsidies for solar systems can lead to second-degree moral hazard– the impulse of installers to increase prices and/or reduce labor input when customers receive subsidies. Employing an instrumental variable strategy using plausibly exogenous variation in the size of subsidy levels to address concerns about self-selection of installers into specific subsidy levels, I quantify the impact of subsidy levels on total costs and electricity output of solar systems in California. The results are consistent with hypothesized drivers of second-degree moral hazard. First, larger subsidy levels are associated with a cost increase when customers receive unconditional upfront subsidies as compared to output-based subsidies. Second, stricter verification rules reduce costs. Third, the association of lager subsidy levels and increased costs is particularly pronounced when third-parties own the solar system and thus receive the subsidy. Finally, costs are larger for government customers and lower for non-profit customers.

Keywords: Solar systems; Credence goods; Subsidies; Asymmetric information; Second-degree moral hazard

JEL Codes: H23; H32; H76; D82; Q42; C26.

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1 Introduction

Many countries use generous subsidy programs to accelerate the adoption of green technologies. To maximize the social and environmental value of each of the tens of billions USD spent on subsidy programs in the US and other countries (International Energy Agency, 2016), subsidy programs should be cost-effective. One key challenge to cost-effectiveness is that markets for energy-transforming technologies are subject to informational asymmetries, as customers often lack the expertise to assess which technology is cost-effective and what work steps are needed to install it. Therefore, professional installers have incentives to exploit their informational advantage, leading to supply-side inefficiencies typical for credence goods, which include overcharging for services or technological components and bad workmanship (Giraudet et al., 2018; Giraudet, 2020; Lanz and Reins, 2021).

The literature on credence goods suggests that third-party reimbursements may cause second-degree moral hazard and thereby increase supply-side inefficiencies (Balafoutas et al., 2017).[1] Because subsidies reduce the cost for customers, installers may be *more* inclined to charge for services which have not been provided, recommend unnecessarily expensive technologies or decrease the quality of labor input (Kerschbamer et al., 2016; Huck et al., 2016; Balafoutas et al., 2017, 2020). The credence component of energy-transforming technologies in combination with the enormous amounts of subsidies spent to foster their adoption therefore has important implications for the cost-effectiveness and design of subsidy programs.

[1] In the context of energy-transforming technologies such as solar systems, first-degree (or demand-side moral hazard) implies that customers install solar systems only because part of the financial burden is taken over by a subsidy. The reduction of the financial burden associated with installing energy-transforming technologies is an often cited reason for promoting their adoption via subsidies (Allcott and Greenstone, 2012) and has the consequence that subsidies may not be targeted to maximize adoption (see related discussion in Allcott et al., 2015; Globus-Harris, 2020). For a discussion on demand- and supply side moral-hazard in the context of energy-efficient retrofits, see for example Giraudet et al. (2018).

In this paper I study how subsidies trigger second-degree moral hazard and hence increase supply-side inefficiencies in markets for solar systems. For this purpose, I use data from the California Solar Initiative (CSI) which is the largest solar subsidy program in California. Idiosyncratic characteristics of the CSI data on subsidized solar systems make it particularly relevant for this research. First, installing solar systems consists of a complex arrangement of different technological components and working steps (Giraudet et al., 2018; Gillingham et al., 2016) which many customers deliberately leave to professional installers. Moreover customers face difficulties to verify whether a system is installed and priced appropriately because the definition of a counter-factual relative to which the electricity output and price is measured is difficult (Giraudet, 2020; Lanz and Reins, 2021). As such, the informational asymmetries between (even technically adept) customers and installers are rather large and solar installers may exploit the scope for supply-side inefficiencies created by the credence nature of solar systems.

The second interesting feature of the CSI program is that it offers regional and chronological variation of subsidies enabling me to identify how the cost and electricity output of solar systems depend on the magnitude of received subsidies. Specifically, the CSI provides subsidies to customers in three different energy supply companies (or investor-owned utilities, IOU) following the aim to generate a total of 1940 megawatts (mW) capacity installed in new solar systems. The subsidy level available to customers is categorized in ten predetermined steps where the transition from one subsidy level step to the next is determined by the of cumulative capacity of mW installed within an IOU.

In the empirical analysis, I quantify the impact of subsidy levels on installation costs and electricity output, using variations of subsidy levels afforded by the design of the CSI program. Following Pless and van Benthem (2019), I estimate linear models using a rich set of fixed effects (FE). Specifically, I employ fixed effects along four axes: i) installer FE to capture time-invariant installer specific characteristics such as their wage and their location, ii) month of installation FE to capture national demand shocks and general time trends for hardware costs, iii) IOU and county FE to capture regional differences in demand and competition among installers and iv) make and model of modules and inverters to control for unobserved differences in the installed technology, such as their quality.

I make use of an instrumental variable strategy to address potential concerns about the endogeneity of actually implemented subsidy levels. The actually received subsidy levels differ from predetermined subsidy levels for some systems and I cannot rule out that installers were able to influence actually received subsidy levels, thereby self-selecting into specific subsidy levels. In particular, some solar systems receive weighted averages of up to 4 different subsidy level steps in contrast to sharp and monotonic decreases of subsidy levels as determined by the CSI design.

To address this concern, I exploit plausibly exogenous variation of predetermined subsidy levels to instrument actually received subsidy levels. In this context, the validity of this instrument rests on two assumptions. First, the predetermined subsidy levels need to be correlated to the actually implemented subsidy levels. This assumption is likely to hold because the predetermined subsidy steps are the predominant factor determining received subsidy levels and the differences between predetermined and actually received subsidy levels is small.

Second, the exclusion restriction implies that the ex ante-determined subsidy level steps do not affect the cost and electricity output of solar systems other than through the actually received subsidy levels. Again, this assumption is likely to hold as even large installers could not influence the total capacity installed within an IOU. I further include the above set of fixed effects in the first stage and thereby control for any between installer, between month, between IOU and county and between technology factors that potentially link subsidy steps to the cost and/or electricity output of systems.

I study heterogeneity of supply-side inefficiencies along four dimensions that have been highlighted as important factors driving second-degree moral hazard (see Balafoutas et al., 2017, for a related discussion). As the first dimension I study in how far the design of subsidies can mitigate second-degree moral hazard. For this purpose, I exploit the fact that the CSI provides two different types of subsidies reducing the installation costs of solar systems. First, unconditional *upfront* subsidies are a one time lumpsum payment increasing in the expected electricity output of a system. Second, *output-based* subsidies are monthly payments depending on the actual monthly electricity output. Output-based subsidies thus provide direct financial incentives to generate and maintain a high electricity output which may spillover and decrease installation costs (Hecht et al., 2012). As a second dimension, I study increased verification of installations and their potential to prevent supply-side inefficiencies (Dulleck and Kerschbamer, 2006; Dulleck et al., 2011). To this end, I exploit a CSI rule imposing a mandatory field inspection for the first two solar systems installed by each installer. Third, I study whether second-degree moral hazard is increased if a system is third-party owned (TPO) and hence installers receive the subsidy. Finally, I study how supply-side inefficiencies depend on whether a system is owned by a commercial, residential, non-profit or governmental customer.

The empirical analysis shows evidence suggesting that second-degree moral hazard is highly relevant in the context of upfront subsidies. I find that a one dollar increase of upfront subsidies is associated with a statistically significant increase of the system cost of approximately $ 0.25 per Watt which is equivalent to a three percent increase of costs at the mean of the sample. Further, I do not find evidence of second-degree moral hazard related to output-based subsidies.

To rule out alternative explanations for the association of larger upfront subsidy levels and increased costs, I provide a set of robustness checks. First, I drop systems which applied in the vicinity of two weeks before and after a transition to a next subsidy step to rule out that customers anticipating this transition and therefore speeding up the application process drive the results (Hughes and Podolefsky, 2015; Pless and van Benthem, 2019). Reassuringly the main conclusions hold when excluding these observations. I second check the robustness of the results to cases where customers with a particularly poor environment for electricity output have opted in the CSI program early, because the investment only amortizes if customers receive large subsidy levels. Afterwards, I employ propensity score matching to compare systems with identical technical components differing in the subsidy level received. Finally, I show that the results are robust to different specifications controlling for time-varying factors.

The results also show significant heterogeneity of supply-side inefficiencies and second-degree moral hazard concerning verification, subsidy recipients and ownership. First, I find that mandatory field inspections reduce the system costs of upfront systems, suggesting that stricter verification of an installer's work limits supply-side inefficiencies (Dulleck et al., 2011). Furthermore, I present evidence that TPO systems are particularly prone to second-degree moral hazard, confirming earlier findings documenting over-reported costs of TPO systems (Podolefsky, 2013). Finally, the results indicate that supply-side inefficiencies are increased when installers face government customers, and limited when installers face non-profit customers as compared to commercial customers.

The findings in this paper contribute to two different kinds of research avenues. The first is a literature assessing the optimal subsidy design to increase adoption and cost-effectiveness of subsidy programs. Existing results show that customers significantly discount future subsidy payments and upfront subsidies are a cheaper way to foster the adoption of solar systems than output-based subsidies (Burr, 2016; Feger et al., 2017; De Groote and Verboven, 2019). These studies do however not account for second-degree moral hazard associated with upfront subsidies and my analysis suggests that related costs need to be accounted for when calculating their cost-effectiveness. Further, the evidence of second-degree moral hazard is in line with results from Borenstein (2017) who finds that installers charge higher prices if customers have larger benefits when from investing in solar systems. The association between larger upfront subsidies and increased system costs can therefore contribute to explaining price variations which are unexplained by observable system characteristics as discussed in Gillingham et al. (2016). The results also relate to pricing differentials in TPO systems (Davidson and Steinberg, 2013; Podolefsky, 2013) and suggest that second-degree moral hazard is particularly pronounced for TPO systems. Finally, second-degree moral hazard provides a parallel explanation for the over-shifting of subsidies found in Pless and van Benthem (2019) as installers may share increased profits with the respective customer.

Second, this paper documents that stylized findings from other credence goods markets are relevant for the market of energy-transforming technologies (Giraudet, 2020; Lanz and Reins, 2021). This paper is the first to document evidence of second-degree moral hazard in the context of energy-transforming technologies. In line with earlier discussions on the potential of strict verification to reduce opportunistic behavior (Dulleck and Kerschbamer, 2006; Dulleck et al., 2011; Balafoutas et al., 2013), I find that mandatory field inspections can reduce cost the cost of solar systems. The results in this paper further confirm heterogeneity of supply-side inefficiencies depending on who bears its costs as supply-side inefficiencies are larger for governmental and lower for non-profit customers (Balafoutas et al., 2013; Gottschalk et al., 2020).

This paper proceeds as follows: in Section 2 I discuss the credence nature of energy-transforming technologies, second-degree moral hazard and resulting consequences for the costs and electricity output of solar systems. Section 3 describes the CSI program. In Section 4, I summarize the data and explain the identification strategy. I present associated results in Section 5 and conclude in Section 6.

2 Solar systems, supply-side inefficiencies and second-degree moral hazard

I illustrate the implications of the credence nature of solar systems building on the framework of Dulleck and Kerschbamer (2006). For simplicity, I assume that there exist two types of solar systems: either those with high quality technological components q_h and those with lower quality technological components q_l. The generated electricity of system i, $V_i(q_i, l_i)$ increases in both, the quality of technology as well as in the quality of labor exerted during the installation l_i, which I assume to be between $[0, 1]$ and $l_i = 1$ indicates perfect installation while $l_i = 0$ indicates a poor installation.

The installer faces a cost for installing a system which increases in both, the cost of technology as well the cost for labor (i.e. $c_i(q_i, l_i)$) and customers pay a price for the system which is increasing in its cost $p_i(c_i)$. The installer's benefit from putting up a solar system hence equals the difference of the price and costs of provided hardware and labor $\pi_i = p_i(c_i) - c(q_i, l_i)$. The customer's benefits from investing in a solar system can be expressed as $\pi_c = V_i(q_i, l_i) - p_i(c_i) + s_i$. In this equation s_i denotes the lumpsum subsidy level customers of upfront systems receive. If customers receive output-based subsidies instead, the subsidy level is multiplied with the electricity output of the system (i.e. $s_i \cdot V_i(q_i, l_i)$.)

Asymmetric information on q_i and l_i (see Giraudet et al., 2018, for a similar assumption) implies that an installer may reduce labor input to save costs which must not necessarily be reflected in a lower prices, because the customer has difficulties to verify work steps and therefore cannot perfectly observe q_i and l_i. If an installer knows that his work will not be verified and if he only cares about his own profits, he thus has the incentive to lower labor input to a minimum and increase the prices charged to a maximum. Such departures from the optimal labor input and fair market prices reflect supply-side inefficiencies which can be summarized under $\sigma \in [0, 1]$ where $\sigma = 1$ indicates full supply-side inefficiencies where the installer provides a poor installation ($l_i = 0$) and charges a maximal price. If the installer provides a perfect installation and charges a fair market price, there are no supply-side inefficiencies (i.e. $\sigma = 0$). Supply-side inefficiencies ($\sigma > 0$) in turn cause a lower $V_i(q_i, l_i)$ and/or a higher $p(c_i)$.

Next, evidence in markets for credence goods suggests that increased verification measures imposed to detecting and punishing supply-side inefficiencies may change the installer's behavior (Dulleck and Kerschbamer, 2006; Dulleck et al., 2011; Balafoutas et al., 2013). Let γ denote the probability of detecting supply-side inefficiencies σ and t denote related punishment. Intuitively, larger verification of the installer's work may work as a threat to lose financial and/or reputation status. The larger γ and t, the larger the expected disutility from supply-side inefficiencies.

Moreover, it has been shown that agents in markets for credence goods care for the customer's benefits, suggesting that installers have some form of social preferences represented by λ (see for example Kerschbamer et al., 2017; Kandul et al., 2020). Looking at the active market for solar systems, it seems plausible that a large heterogeneity in λ exists, implying that many installers care for the customer's benefits and therefore provide flawless services (see for example Kerschbamer et al., 2017). At the same time, differences in the customer owning the system may affect λ. When installers think about who bears the consequences of supply-side inefficiencies, they may for example want to reduce the burden for residential customers who they personally know (i.e when. λ is large) compared to more abstract entities with several stakeholders and financiers such as governmental and commercial customers (see Balafoutas et al., 2017, for a discussion of how social distance may affect the behavior of installers).

Adding these insights to the framework of Dulleck and Kerschbamer (2006), the objective of the installer can be written as follows:

$$\pi_i = p(q_i, l_i) - c(q_i, l_i) - \gamma t\sigma + \lambda(V_i(q_i, l_i) - p(q_i, l_i) + s_i). \tag{1}$$

The literature on credence goods further suggests that an installer may alter his behavior conditional on the magnitude of the subsidy. For solar systems, Davidson and Steinberg (2013) and Podolefsky (2013) have documented that some TPO installers inflate the cost of residential solar systems to reap larger federal investment tax credits. Several installers have been accused of over reporting the cost of systems as much as 10 percent of the fair market value, resulting in 25 millions of excess investment tax credits (ITC) and federal investigations of the accused installers.[2] In this simple framework, such second-degree moral hazard implies that an increase in the subsidy s_i reduces financial burden for customers and installers may therefore react by *further* reducing labor input which leads to reduced electricity output or increasing prices.

Note that I study two different kinds of subsidies which are either paid upfront as a lumpsum (s_i) or are based on actual electricity output and paid per kWh generated ($s_i \cdot V_i(q_i, l_i)$). Output-based subsidies are therefore increasing in electricity output, providing a direct financial incentive for high quality installations. This may affect the labor input of an installer and may also spillover to his pricing behavior (Holmstrom and Milgrom, 1991).

[2] The investment tax credit, is a 30 percent tax credit which was granted to all solar residential and commercial systems installed in the US from 2006-2019. It has been reduced to 26 percent in 2020 and is projected to decrease further in the coming years.

3 The California Solar Initiative program

The California Solar Initiative (CSI) program provides a useful setup where predetermined subsidy levels are assigned to different customers, enabling me to analyze the associated relation with costs and electricity output of such systems. This section starts with a general description of the program. Afterwards, I describe which features of the CSI are exploited to study heterogeneity of supply-side inefficiencies and second-degree moral hazard related to different subsidy types, increased measures of verification and differences in the ownership. Finally, I describe the main outcome variables of the empirical section: cost and electricity output.

3.1 Program description

The CSI subsidy program rolled out in 2007 using a budget of $2.167 million for the goal to install 1940 mW within 10 years. All customer segments could apply for the program including residential, commercial, government and non-profit customers. The subsidy level available to customers is determined by the cumulative capacity of already installed systems within the IOU of the customer. Once a certain threshold of cumulative mW in an IOU is passed, the subsidy level decreases. In particular, the CSI provides subsidies to customers in investor-owned utility territories of Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E). Table 1 provides an overview of the subsidy levels as per the design of the CSI. After the first 50 mW in each IOU have been attributed under another program (Lilly and Simons, 2006), passing the predetermined threshold of mW installed leads to a sharp and monotonic decline of subsidy levels in the IOU.

The actual implementation of subsidy levels however differed from the theoretical design. Figure 1 provides an overview of the implemented subsidy levels across IOUs

Table 1: CSI subsidy levels

		Upfront ($ per Watt)		Output-based ($ per kWh)	
mW Step	**MW in step**	**Residential/ Commercial**	**Gov't/ Nonprofit**	**Residential/ Commercial**	**Gov't/ Nonprofit**
1	50	n/a	n/a	n/a	n/a
2	70	2.5	3.25	0.39	0.5
3	100	2.2	2.95	0.34	0.46
4	130	1.9	2.65	0.26	0.37
5	160	1.55	2.3	0.22	0.32
6	190	1.1	1.85	0.15	0.26
7	215	0.65	1.4	0.09	0.19
8	250	0.35	1.1	0.05	0.15
9	285	0.25	0.9	0.03	0.12
10	350	0.2	0.7	0.025	0.088

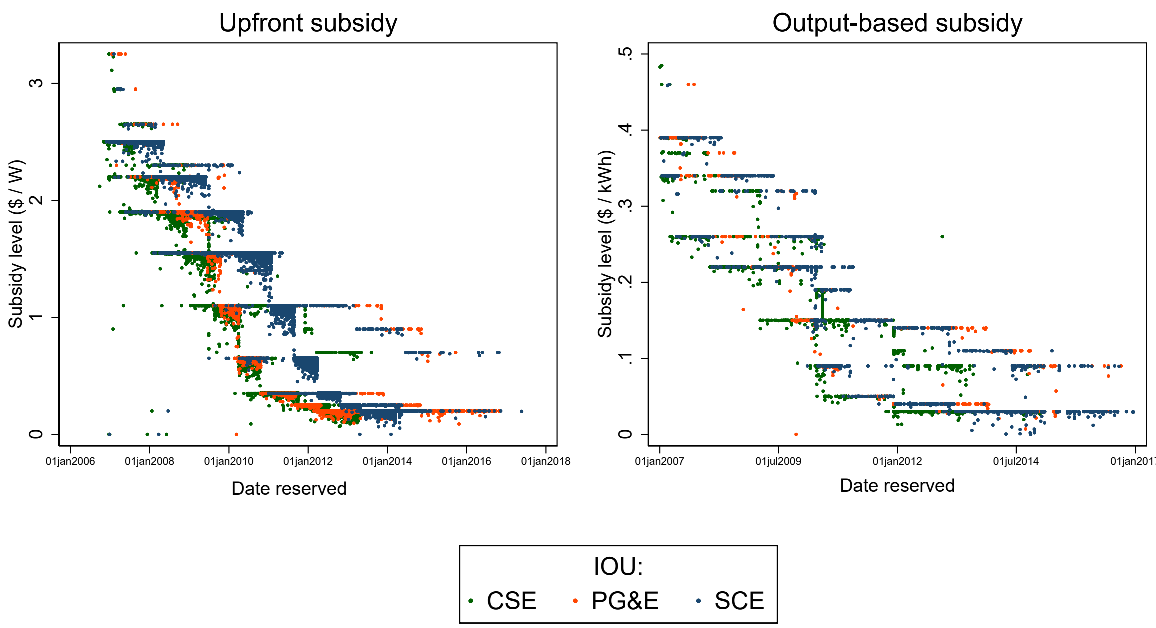
Notes: Table 4 of California Public Utilities Commision (2017)

and time. In the left panel, I show the evolution of upfront subsidies and in the right panel, I show the evolution of output-based subsidies. One can see that for example in January 2010, many different upfront subsidy levels were attributed to different solar systems in all IOUs. Contrasting the unique subsidy levels in each MW step, some systems receive weighted averages of up to four different predetermined subsidy levels. In addition, subsidy levels do not monotonically decline in time, but some systems which have applied in the same IOU at later point in time receive a higher subsidy rate.[3] A similar picture emerges for output-based subsidies in the right panel.

While the subsidy levels attributed to systems is predetermined by the mW step, the CSI multiplies this subsidy level with either a measure for the expected or actual electricity output depending on whether customers receive upfront or output-based subsidies. Therefore, the total amount of subsidies depends on the system size as this is related an increased expected and actual electricity output. Accordingly, installers can increase the total subsidy amount a customer receives by installing extensive systems. In such situations, installers can offset part of the financial consequences of second-

[3] The CSI handbook does not provide an explanation for these observations which contrast the theoretical design of the CSI. Presumably, the fact that some systems receive a weighted average of several subsidy levels could be either due to cancellation of systems and freed capacity under step already exhausted or an adjustment of CSI subsidies if systems receive other benefits (Hughes and Podolefsky, 2015).

Figure 1: Evolution of subsidy levels



Notes: Upfront and output-based subsidy levels over time and IOU's.

degree moral hazard by maximizing the subsidy transfer to the customer.

To avoid the installation of unreasonably sized systems the CSI imposed rather strict limitations to substantiate a system's size and ensure that a system is sized such that it optimally serves the customers needs. First, a system should primarily offset the applicants own energy consumption, meaning that the annual expected electricity output must not be larger than the sum of energy consumption within last twelve months. Second, no applicant may receive a total amount of subsidies exceeding the total cost of the system. Third, there is a cost cap for applications implying that the cost per Watt may not be larger than the 12 month rolling average of the cost per Watt of other systems plus one dollar.

Studying the distribution of systems around two arbitrary thresholds provide information whether installers strategically influence the size of systems. First, systems smaller than five kW were not required to hand in a substantiation of the system size when applying for the CSI. Second, systems smaller than ten kW did not have to pay an application fee.[4] Figure A1 in Appendix A presents the size distribution of upfront systems in the range between zero and 30 kW in the left panel and between four and twelve kW in the right panel. There are not disproportionately many systems sized just below five or ten kW, affirming that the system size is determined by the customer's needs rather than strategic considerations.

3.2 Upfront and output-based subsidies

To study how subsidies affect second-degree moral hazard, I exploit the fact that the CSI offered two different subsidy types. The "Expected Performance Based Buyout" (or *upfront* subsidy) is intended for residential and small business customers installing a

[4] For other system sizes the application fee starts from 1250 USD for systems up to 50kW and amounts to 20000 USD for systems 500-1000 kW. Note that this fee is refunded once the system is installed.

system with less than 30 kW and take the form of a lumpsum transfer depending on the expected electricity output of the system. Customers installing a system sized larger than 30kW were obliged to apply for "Performance Based Incentives" (or *output-based* subsidy) which take the form of a fixed rate of $ per actual kWh generated by the system for five years.[5] Note that customers installing a system with more than 10kW could opt to apply for a output-based subsidy. As discussed in Appendix A, the subsidy type is predominantly determined by the system size rather than strategic considerations, alleviating concerns about strategic self-selection into subsidy types.

While the general idea behind the implementation of upfront and output-based subsidies are the same, some subtle differences in their design have important implications for the analysis of second-degree moral hazard. First, output-based subsidies provide a direct financial incentive to generate and maintain a high electricity output. Installers who care for the outcome of their customer (i.e. $\lambda \neq 0$ in Equation 1) should respond with higher quality installations. Whether these incentives further spillover to unincentivized outcomes, such as the price charged for the system, has received a lot of attention (Holmstrom and Milgrom, 1991; Jenkins Jr et al., 1998). More recent evidence suggests that spillovers can improve the outcome of unincentivized tasks when they are performed simultaneously (Hecht et al., 2012) suggesting that in this context, output-based subsidies could also reduce the price of installations.

Also payment and verification procedures differ for both types of subsidies. First, output-based subsidies are paid over several months while the upfront subsidy is a one time lumpsum transfer. De Groote and Verboven (2019) find that future payments of output-based systems are profoundly discounted, suggesting that the net present value

[5] Not all output-based systems report electricity output data for five years after installation. When the CSI budget faded out, system not having completed the five-year reporting timeline received a buyout determined on the actual electricity output up to this time.

of output-based subsidies is smaller.[6] Second, the electricity output of output-based systems needs to be reported to the CSI by a performance data provider, which is an entity ensuring that the reported data on electricity output is accurate. Also the output metering technology of solar systems receiving an output-based subsidy systems needs to provide an accuracy of measuring of +- two percent compared to +- five percent for upfront systems.[7] These differences between upfront and output-based subsidies suggest that output-based subsidies could be more robust to supply-side inefficiencies and second-degree moral hazard.

3.3 Increased verification

The first two solar systems installed by each installer are subject to an onsite field inspection which serves the goal to detect differences between the onsite technical calibrations of the system and those stated in the application form.[8] Mandatory field inspections include checking that equipment is installed as documented in the application (i.e. quantity and make of modules and inverters, a systems tilt, azimuth, shading and standoff height) as well as whether the system is operational and its electricity output is reasonable. Finally, if subsidy payments resulting from onsite inspections and those calculated in the application form documentation differ by more than 10 percent, the solar system and its installer can be dismissed from the program.

[6] Similarly, focusing theory suggests that principals overweight concentrated upfront payments compared to dispersed output-based payments (Kőszegi and Szeidl, 2012; Dertwinkel-Kalt et al., 2019). Related evidence suggests that the differences in the concentration of payments could render the perception of total output-based subsidies smaller.

[7] Further, all output-based systems (as well as upfront systems larger than 10kW) are obliged to provide proof of project milestone documenting initial installation steps and reassuring that the system is installed as outlined during the application. In addition, such systems need to contract services of a output monitoring and reporting service, to ensure that 15 minute time interval data can be provided to the program administrator.

[8] The program administrator has the right to audit additional systems according to his own assessment. These audits are either performed online, via telephone or onsite.

This rule increases the probability γ of detecting supply-side inefficiencies and installers face commercial consequences after detection (i.e. $t > 0$). In turn installers may limit supply-side inefficiencies in order to prevent financial and reputational consequences in case of detection (cp. Balafoutas et al., 2013; Giraudet et al., 2018, who find that increased verification reduces increased costs and supply-side inefficiencies are specifically pronounced in domains defined as *hard to observe*). Assessing differences in supply-side inefficiencies between the first two and all other systems installed by the same installer, reveals how increased verification contributes to more performing solar systems.

3.4 Subsidy recipients

Instead of buying a solar system, both upfront and output-based customers in California can choose to lease a solar system from a third party (Podolefsky, 2013; Pless and van Benthem, 2019).[9] In this case, TPO installers pay the installation costs and receive the final subsidy (i.e. they directly appropriate s_i Equation 1). The objective function of an installer suggests that this is equivalent to an increase in the subsidy which should thus lead to an increase of second-degree moral hazard. At the same time it seems straightforward that TPO installers who bear the upfront installation cost of a system want to minimize it. In contrast, it has been shown that TPO firms have inflated the costs of residential solar systems (Davidson and Steinberg, 2013; Podolefsky, 2013). Pless and van Benthem (2019) somewhat surprisingly find a more than complete pass-

[9] If customer choose to lease a system, they can decide between a pure leasing contract or a power purchase agreement (PPA). In a pure leasing contract, the customer pays a monthly leasing rate to the third party and owns the electricity output. In a PPA contract, the customer pays monthly rate for his electricity consumption and the third party owns the electricity output. The contract types mostly differ with respect to who is entitled to the benefit of excess output fed into the system. Under either contract type, the third party pays for the installation and maintenance of the system and customer hence do not bear the upfront costs (see Davidson et al., 2015, for a detailed discussion of pure lease and PPA contracts). In the dataset, I can identify the systems owned by a third party but I cannot identify whether they have a leasing or PPA contract.

through of upfront subsidies to residential customers of TPO systems and attribute this effect to imperfect competition on the market for TPO systems in combination with a sufficiently convex demand curve. This finding suggests that increased costs were not passed on to customers in form higher leasing rates. The second-degree moral hazard problem of installers provides a parallel explanation for more than complete pass-through as TPO installers who may increase the total amount of subsidies then split increased profits from supply-side inefficiencies with customers (see Gillingham et al., 2016, for a similar reasoning).

Differences between HO and TPO systems during the application procedure further suggest that HO systems are subject to stricter verification measures. HO systems need to hand in an executed agreement to purchase and install the solar system documenting the scope of work, the total agreed price as well as the quantity, make and model of solar system components to be installed. While TPO system must hand in legally binding contracts documenting the scope of work, terms and prices, they do not have to determine the make and model of solar system during installation. Lower verification measures in combination with evidence on cost inflation of TPO systems hence suggest that TPO systems are particularly prone to supply-side inefficiencies and second-degree moral hazard.

3.5 Type of ownership

Furthermore, installers in the sample face commercial, residential, non-profit and governmental customers. This enables me to study differences behind the entities owning solar systems which differ with respect to financial resources and social distance (i.e. heterogeneity in λ). Following Balafoutas et al. (2017), installers may be more inclined to increase costs when customers are perceived as wealthier and the financial consequences are borne by an anonymous entity compared to a residential customer with whom interaction is more direct and personal.

Evidence on distributional preferences of agents in markets for credence goods suggests that supply-side inefficiencies are reduced when they have larger financial consequences for the customer (Kandul et al., 2020). If installers perceive non-profit and residential customers as less financially endowed and therefore have a higher valuation for their benefits (i.e. a larger λ) compared to commercial and government customers, one would observe differences in supply-side inefficiencies and second-degree moral hazard depending whether customers can be attributed to the commercial, government, non-profit or residential sector.

3.6 Measures of cost and electricity output

To document supply-side inefficiencies and second-degree moral hazard in the context of solar systems this paper first analyses the costs solar systems under different subsidy levels. In line with technical conventions, the total system costs are divided by its size. In particular, the CSI rating is used to determine the cost per Watt as this measure reflects the system's real world electricity generating potential (see Podolefsky, 2013; Hughes and Podolefsky, 2015; Dong et al., 2018; Pless and van Benthem, 2019, for a similar procedure).[10] The CSI data provides the total eligible project cost for each system, which include costs for the technological components, construction and installation costs, engineering and design costs, interconnection cost as well as warranty

[10] We note that the CSI data reports three different measures of a system's size. The nameplate measures the electricity generating potential under standard test conditions. The CEC-AC rating is based on more realistic assumptions on the location of the system such as wind speed and ambient temperature. The CSI rating equals the CEC-AC rating multiplied by the design factor of the system which reflects the particular generation potential of a system's environment such as shading and orientation.

and maintenance costs.[11] While the costs for technological components may be easily verifiable, the idiosyncratic environment of each system demands specific installation and maintenance work-steps where installers likely have some range to exploit with regard to pricing.

The second variable of interest where supply-side inefficiencies in form of reduced labor input are likely to manifest themselves is the electricity output of solar systems. Again, the monthly electricity output is divided by the CSI rating of the system's size (see Wang and Sueyoshi, 2017, for a discussion). This measure hence can hence be interpreted as the conversion efficiency of the system and indicates how much electricity is actually generated per Watt of installed hardware. The CSI data provides monthly data on the electricity output of output-based systems installed between 2006 and 2016.[12] Reasons for a lower electricity output per Watt include exogenous factors like cloudy or hot weather and also extreme weather conditions which cause damage to the systems. Because I analyze a large set of systems over an average time of 30 months, these exogenous factors can be viewed as hitting each solar system with similar probability (note that the identification strategy used in this paper controls for regional weather and climate differences by including county fixed effects). Besides these exogenous factors endogenous factors such as the workmanship of the installer, particularly the configuration quality of inverters and modules are crucial determinants of a solar system's electricity output (Spertino and Corona, 2013).

[11] Adjusting the total costs for the ITC is akin to a linear transformation, as all systems installed during the sample period receive a 30 percent tax credit. Consequently, this procedure would not affect the results. See Pless and van Benthem (2019) for further information.

[12] The CSI does not provide output data for upfront systems.

4 Data and empirical strategy

I first provide a summary of the data in Section 4.1 and then present the identification strategy to investigate supply-side inefficiencies and second-degree moral hazard in Section 4.2.

4.1 Data summary

The information on the applicants of each solar system provides a rich set of system characteristics. Table 2 presents summary statistics of the data for each year of the sample time (2007 to 2016).[13] The evolution of system characteristics for systems receiving upfront subsidies is shown in the upper Panel A, for systems receiving output-based subsidies in the lower Panel B.

The first three rows of each panel show the mean, minimum and maximum subsidy level in a given year. In line with Figure 1, both upfront and output-based subsidy levels considerably vary within each year. The next two rows of each panel show the average cost per Watt and in total. As the fixed costs for the installation of solar systems are distributed over the system size, the cost per Watt for smaller upfront systems tends to be larger (see also Gillingham et al., 2016, for a detailed discussion). Importantly, the cost per Watt as well as the total cost is declining over time for both subsidy types. This trend is in line with a decrease of hardware costs in recent years. Because the CSI subsidy levels also decrease over time, controlling for changes in time-varying factors affecting the cost and electricity output of solar systems is crucial when estimating

[13] Note that I drop solar systems which have not been installed at the time of the data access. Also, systems without entries for the subsidy level, total cost or date of reservation were dropped in the data. Further, when CSI incentives in an IOU phased out, all output-based systems who have not yet completed their five year reporting timeline received a lump sum buyout. For such systems, the expected electricity output for the remaining months was calculated and gratified with the subsidy level. I drop these observations as these do not represent real electricity output but predicted electricity output.

Table 2: Summary statistics

Panel A:					Upfront subsidy					
Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean subsidy level ($/W)	2.40	2.02	1.58	1.03	0.60	0.30	0.21	0.20	0.21	0.22
Min subsidy level ($/W)	0.90	0.20	0.65	0.89	0.20	0.07	0.07	0.05	0.08	0.15
Max subsidy level ($/W)	3.25	2.65	2.30	2.30	1.55	1.10	1.10	0.90	0.70	0.70
Mean cost per Watt ($/W)	8.2	8.3	7.8	7.1	6.6	5.4	4.9	4.5	4.4	4.3
Mean total cost in 1000 $	51.5	46.6	44.2	39.0	35.1	32.2	31.0	29.9	32.7	33.3
Mean size in kW	6.4	5.7	6.1	5.8	5.6	6.1	6.5	6.8	7.8	8.1
Mean number of modules	34	30	30	27	25	24	25	25	28	29
Mean number of inverters	1	1	2	4	5	6	8	8	11	9
Mean previous systems	122	462	608	995	1557	3010	4722	5331	3540	5417
First two=1	9.0	4.4	5.4	3.6	1.9	1.0	1.1	0.9	1.8	1.6
Mean designfactor	0.95	0.94	0.94	0.94	0.95	0.94	0.94	0.95	0.95	0.96
TPO=1	7.1	14.4	14.4	30.9	53.1	71.9	66.7	57.6	40.4	35.6
Commercial	2.8	2.8	1.2	1.8	1.0	0.9	0.8	2.2	4.4	10.6
Government	0.6	0.6	1.1	0.4	0.8	0.6	0.1	0.1	0.0	0.7
Non-profit	1.1	0.7	0.5	0.5	0.3	0.2	0.2	0.9	3.2	2.5
Residential	95.5	96.0	96.6	97.3	98.6	98.9	98.9	96.8	92.4	86.3
Observations (141,792)	6,477	9,701	13,334	18,994	21,692	31,691	30,416	5,677	498	160
Panel B:					**Output-based subsidy**					
Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean subsidy level ($/kWh)	0.35	0.28	0.24	0.15	0.09	0.06	0.06	0.05	0.05	0.04
Min subsidy level ($/kWh)	0.23	0.16	0.09	0.04	0.02	0.01	0.01	0.00	0.02	0.01
Max subsidy level ($/kWh)	0.49	0.39	0.34	0.32	0.26	0.26	0.14	0.11	0.11	0.09
Mean cost per Watt ($/W)	7.8	7.6	6.8	5.5	5.0	4.4	3.9	3.4	3.2	2.9
Mean total cost in 1000 $	2107.3	1523.4	1433.1	1556.6	1196.9	1013.7	813.8	1220.5	1215.0	1055.4
Mean electricity output (mWh)	39.2	28.3	32.5	40.7	36.1	33.1	30.2	48.3	59.6	47.6
Mean conversion efficiency (kWh/W)	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.12	0.12	0.12
Mean size in kW	295.2	213.6	245.6	302.3	265.7	253.0	235.0	379.0	478.2	403.0
Mean number of modules	1471	1046	1195	1258	1046	919	819	1260	1978	1257
Mean number of inverters	2	3	3	18	5	14	34	39	17	26
Mean previous systems	34	150	229	640	1758	1624	2166	3036	763	4473
First two=1	10.4	6.4	7.3	7.4	4.6	3.9	3.9	4.3	5.0	3.5
Mean designfactor	1.03	1.02	1.00	0.98	0.97	0.95	0.96	0.99	0.99	0.98
TPO=1	51.4	33.1	21.0	37.6	28.2	31.5	39.7	36.2	15.1	30.6
Commercial	55.6	37.7	33.0	30.9	39.1	41.0	39.5	53.1	63.9	64.7
Government	15.3	21.5	23.4	54.4	44.3	47.8	44.0	34.9	21.9	24.7
Non-profit	2.9	6.1	4.9	6.4	8.5	7.9	14.2	10.6	14.3	10.6
Residential	26.9	34.7	38.7	8.3	8.1	3.3	2.3	1.5	0.00	0.00
Observations (4,474)	385	324	385	1,017	503	546	570	538	119	85

Notes: Averages over year by subsidy type. I do not report summary statistics for 2006 and 2017 because there were only a few applications in these years.

second-degree moral hazard.

The absolute electricity output and electricity output per Watt of output-based systems is then shown in Panel B. The absolute electricity output closely follows the system size. At the same time, the electricity output per Watt remains rather constant, suggesting that there were no major changes of exogenous influences (i.e. solar radiance, ambient temperature etc.) or endogenous factors (i.e. the setup and configuration of technical components) on the conversion efficiency during the sample period.

Next, the size in Watt shows no specific time trend for both types of subsidies. While the number of modules seems to be rather constant, the number of inverters installed in each system is increasing over time. This is in line with the trend that the peak kW (i.e. the maximum kWh generated per module) has increased over time and fewer modules are necessary to reach a given level of electricity output. The next row shows the number of systems installed by an installer which serves as an indicator for his experience (Bollinger and Gillingham, 2019). This measure is higher for upfront systems compared to output-based systems. This is in line with the increased overall number of upfront systems. Afterwards, the fraction of systems subject to a mandatory field inspection is shown. The decreasing trend of this variable implies that there are not many new installers joining the market during the sample time.[14]

The designfactor expresses a system's effective size measured by the ratio of expected output of the proposed system to expected output of a baseline system. It accounts for idiosyncratic characteristics of the system such as the orientation, azimuth, shading. While the designfactor of systems does not show a specific pattern of change over time, output-based systems have a slightly larger designfactor than upfront systems. This can be attributed to slight differences in calculating the designfactor for upfront and output-based systems (California Public Utilities Commision, 2017, Section 2.2.5). The regressions in the empirical analysis, are run separately for both subsidy types, implying that these differences do not affect the estimation.

Next, the share of TPO systems receiving upfront subsidies is increasing during the sample period, which corresponds to the increasing penetration of TPO firms in

[14] For both subsidy types a drop of the previously installed systems in 2015 can be observed. As there are much less observations for this year, this suggests that some new installers joined the program in 2015 and thereby decreased the average number of previous systems installed. This is in line with the peak of first two systems installed in this year.

residential markets observed in Pless and van Benthem (2019). The share of TPO contracts among output-based based subsidies is initially larger, and then remains rather constant during the sample period.

In the next four rows the distribution of ownership for both subsidy types is presented. While upfront systems are predominantly owned by residential customers, output-based systems are mostly installed by commercial and government customers. This is in line with the intended allocation of upfront subsidies to smaller customers.

4.2 Identification strategy

To estimate the association of subsidy levels and cost/electricity output per Watt, I employ the following regression specification which is adapted from Pless and van Benthem (2019) and is applied to the data on upfront and output-based systems separately:

$$Y_i = \alpha + \beta_i s_i + \varphi_u + \delta_k + \omega_c + \varsigma_f + X_i \phi + \mu_t + \epsilon_i \tag{2}$$

where Y_i denotes the cost or electricity output per Watt for system i, s_i the subsidy level for system i. I further employ IOU φ_u and county fixed effects δ_k to control for regional and local time invariant factors such as local competition among installers which could affect the cost of systems (Gillingham et al., 2016). Importantly, I make use of installer fixed effects ω_c to eliminate potential bias due to heterogeneity of costs at the installer level such as wages or travel costs of installers. ς_f indicates the make and model f of modules and inverters installed in system i and by employing them, I control for time invariant characteristics of the installed technology, such as its quality. ϵ_i denotes a random error term. Standard errors are clustered at the zip code level and thereby correct for potential correlation of data errors within regional CSI offices (Podolefsky, 2013; Pless and van Benthem, 2019).

X_i is a vector of control variables which includes the number of modules and inverters as well as a measure of the experience of installers calculated by how many systems installer c installed previous to system i (see Bollinger and Gillingham, 2019; Gillingham et al., 2016, for a discussion of the effects of learning by doing). I further add a variable indicating the age of the solar system in years when applying specification 2 to the monthly data on electricity output to control for wear and tear of systems over time.

Finally, μ_t is a dummy variable for the month t in which system i was installed to control for monthly changes of general cost trends such as technological progress. When I run specification 2 on the monthly data of electricity output, μ_t is a dummy variable for the month t of the electricity output of system i to account for seasonal differences.

There is, however, a potential issue with specification 2 because the actual received subsidy levels differed from the predetermined subsidy levels for some observations for reasons which were not explained in the CSI program (California Public Utilities Commision, 2017). I can thus not rule out that installers are to influence the subsidy level and therefore self-select into specific subsidy levels. To address this concern, I exploit plausibly exogenous variation of the predetermined subsidy level as part of an instrumental variable strategy. In the first stage, I instrument the actually received subsidy level with the predetermined subsidy level depending on the cumulative mW installed within an IOU (see Table 1). Because the actual allocation of subsidy levels was mostly in line with the predetermined schedule, predetermined subsidy levels are a good predictor of actually received subsidy levels.

Further, the exclusion restriction requires that the instrument affects the cost and electricity output of systems only through the subsidy level. Again, this assumption is plausible as even large installers did not have the market power to influence the total capacity installed within a IOU, preventing them from influencing the transition process from one subsidy level step to another. Importantly, the exclusion restriction is conditional on a set of control variables and I include the above mentioned fixed effects in the first stage. I thereby control for any between installer, between month, between IOU and county and between technology factors that potentially link subsidy steps to the cost and/or electricity output of systems. These notably include installers who only apply for CSI subsidies under earlier steps when subsidy levels are larger, regional differences in demand factors determining the transition speed to next subsidy steps or co-movement of subsidy steps and declining hardware costs due to technological progress.

Formally, the received subsidy level (see Figure 1) is instrumented with the predetermined subsidy level depending on the cumulative mW installed as presented in Table 1:

$$Z_i = \textit{predetermined } s_i \tag{3}$$

Consequently, the first stage regression can be written as:

$$s_i = \eta + \theta Z_i + \vartheta_u + \iota_k + \kappa_t + \xi_c + \varrho_f + X_i \tau + \nu_i. \tag{4}$$

Using this instrumental variable approach, the second stage estimate β accounts for potential endogeneity of the actually received subsidy levels. The estimate is further based on within month, within IOU, within county, within installer and within technology variation of subsidy levels. Controlling for additional factors which potentially influence the costs and electricity output per Watt, I interpret β as the causal relation between a one dollar subsidy increase and associated changes of the cost and electricity output per Watt of solar systems.

I complement this identification with a set of robustness checks. First, Hughes and Podolefsky (2015) as well as Pless and van Benthem (2019) note that customers could to some extent anticipate subsidy step transition dates and therefore speed up the application process to receive higher subsidy levels. I therefore follow Hughes and Podolefsky (2015) and Pless and van Benthem (2019) and drop systems which applied in the vicinity of two weeks before and after a subsidy level drop. I then apply the instrumental variable strategy this subset of data.[15]

Second, one could argue that customers with a particularly poor environment for solar electricity generation have opted in the CSI program early, because only high subsidy levels make the investment for such customers profitable (see Globus-Harris, 2020; Gilbert et al., 2019, for a related discussion of additionality effects). These systems may then be associated with larger installation costs and lower electricity output while receiving larger subsidies. Note that the design factor provides an adequate measure for a systems electricity output potential and it does not show a specific co-movement with the subsidy level (see Table 2). Further, I use the CSI rating to calculate the dependent variables and this rating takes into account differences in the design factor (see Section 4.1). To rule out the above explained scenario as an alternative explanation for the effect, I rerun the 2SLS specification in equation 2, calculating the the cost per Watt under standard test conditions (i.e. a system's nameplate) and explicitly control for the design factor.

[15] The possibility that customers are able to decide on which side of the threshold for a subsidy step in combination with the irregularities concerning the actually received subsidies impedes me from using a regression discontinuity design. The instrumental variable strategy however mimics the first stage regressions which one would have performed to determine abrupt subsidy level changes in the vicinity of threshold for a transition to a next subsidy step.

Third, customers who self-install their system have straightforward incentives to maximize electricity output of a system while minimizing its costs (see Section 2). Consequently, self-installed systems should not be prone to second-degree moral hazard. To study this hypothesis, I apply the 2SLS specification to the subset of self-installed systems.

Fourth, I report an estimate of propensity score matching, thereby providing an alternative strategy to address the potential concern that the assignment of the subsidy level is correlated to other determinants of a system's cost. I define systems receiving a subsidy levels larger above the median as treated (i.e. $D_i = 1$). The estimate is based on nearest neighbor matching, implying that a treated system is matched with an untreated system on the same observable characteristics including the make and model of modules and inverters and the installation date (i.e. both systems installed in the same quarter of a year). I estimate the treatment effect on the treated (ATT) as $\Delta^{TT} = E[Y_{it}(1) - Y_{it}(0) \mid D_i = 1]$, where $Y_{it}(1)$ denotes the potential cost outcome of system i at quarter t if treated and $Y_{it}(0)$ denotes the potential cost outcome if not treated. The ATT hence provides information in how far the cost per Watt of identical systems depends on the subsidy level its customer receives.

Finally, the identification of second-degree moral hazard crucially hinges on controlling for technological progress and other time-varying factors that affect the cost and electricity output of solar systems. I therefore re-estimate the 2SLS specification 2 adding linear, quadratic and cubic time trends instead of employing monthly fixed effects.

I then study whether the association between subsidy levels and costs/ electricity output is affected by increased verification of the installer's work, the recipient of subsidies and the ownership of systems. For this purpose, I interact the subsidy level s_i in specification 2 with a variable indicating whether i) a system is among the first two installed and therefore subject to a mandatory field inspection, ii) the system is owned by a third-party who receives the subsidies, and iii) the system is owned by a commercial, government, non-profit or residential customer. This procedure requires that I instrument each interaction term with the predetermined subsidy level interacted with the category of the indicator variables, resulting in several first stage regressions. To ease the interpretation of the interaction terms, I further center the subsidy level variable around its mean. Hence, interaction terms can be interpreted as the association of subsidy levels and cost/ electricity output at the mean subsidy level of the sample.

5 Empirical results

I start this section by presenting the impact of subsidy levels on the cost and electricity output of solar systems. The framework in Section 2 further implies that i) installers may limit supply-side inefficiencies if they more likely to be detected, ii) second-degree moral hazard may be more pronounced if installers receive the subsidy and iii) installers care about who bears how much of the financial consequences of their opportunistic actions. I study these hypotheses and present estimation results showing heterogeneous effects related to increased verification measures (Section 5.3.1), the subsidy recipient (Section 5.3.2) and ownership of solar systems (Section 5.3.3).

5.1 Subsidy levels and costs of solar systems

Table 3 shows regression results for Equation 2 when the outcome is cost per Watt of upfront systems.[16] In column (1), I report OLS estimates for the linear model presented

[16] Throughout this section, I use the Stata package REGHDFE to estimate linear models with multiple fixed effects (Correia, 2019). I exclude singleton groups (i.e. groups with only one observation) to avoid underestimated standard errors which could bias statistical inference (Correia, 2015). Keeping singleton groups does not affect the qualitative conclusions.

Table 3: Cost per Watt of upfront systems

	All obs. included		Drop obs. +- 2 weeks	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
Subsidy level	0.231*** (0.033)	0.247*** (0.038)	0.261*** (0.034)	0.250*** (0.039)
N	136,876	136,876	125,038	125,038
1st-stage partial F-stat.	-	52717.1	-	50239.1

Notes: The outcome variable is cost per Watt of upfront systems. All specifications include fixed effects for the IOU, county, month, installer as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters as well as an indicator for the number of systems a installer has installed before system i. The 1st stage partial F-statistics for the instrumental variables are derived from first- stage regression results reported in Appendix B, Table B1. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

in specification 2. In column (2), I report results for the same model estimated with 2-stage least squares (2SLS) where the actually received subsidy level is instrumented with the predetermined subsidy level as shown in equation 3. In columns (3) and (4) I repeat this sequence dropping customers who applied within two weeks of subsidy level drop dates.

In all specifications, the difference in cost per Watt associated with higher subsidy levels is large and statistically significant. The OLS and 2SLS estimates in columns (1) and (2) are similar in size and significance, suggesting that endogeneity does not bias the OLS estimation. Using the predetermined subsidy level as an instrument for the actually received subsidy level has further significant explanatory power indicated by large first-stage F-statistics. Dropping observations within two weeks of subsidy step transitions in columns (3) and (4) does not change the qualitative conclusions.

These results suggest that a one dollar increase of upfront subsidies is associated with an increase of the system cost of approximately $ 0.25 per Watt. Given an average

Table 4: Robustness checks for the cost per Watt of upfront systems

	Designfactor	Self-installed	NN matching	Linear	Quadratic	Cubic
	(1)	(2)	(3)	(4)	(5)	(6)
Subsidy level	0.270***	0.239	0.147***	0.333***	0.347***	0.366***
	(0.036)	(0.349)	(0.017)	(0.030)	(0.030)	(0.029)
N	136,877	1,266	26,412	136,877	136,877	136,877
1st-stage partial F-stat.	52800.1	1411.9		50687.4	51985.8	53594.4

Notes: The outcome variable is cost per Watt of upfront systems. All specifications include fixed effects for the IOU, county, month, installer as well as for make and models of modules and inverters. In columns 4 to 6, I drop monthly fixed effects and add a variable indicating the month (either linear, quadratic or cubic) of reservation since the start of the CSI program. Further, all specifications include controls for the amount of modules and inverters as well as an indicator for the number of systems a installer has installed before system i. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results reported in Appendix B, Table B2. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

cost of 7.6$ per Watt (see Panel A of Table 2), a one dollar subsidy increase would hence lead to a three percent increase of the system costs at the mean of the sample. This suggests that larger subsidy levels lead to second-degree moral hazard and thereby significantly increase the costs of upfront systems.

Robustness checks for these estimates are presented in Table 4. Column (1) presents estimates when the cost per Watt of systems is calculated using its nameplate and explicitly controlling for the designfactor; in column (2) I run specification 2 on the subset of self-installed solar systems; in column (3) I report an estimate of nearest neighbor (NN) matching; and columns (4) to (6) I replace monthly fixed effects with liner, quadratic and cubic time-trends.

I find that the association of higher subsidy levels and increased system costs is unaffected when controlling for additionality effects (column 1), suggesting that the results are indeed driven by second-degree moral hazard. Furthermore, this association is insignificant if customers install their own solar systems (column 2). Using propensity score matching (column 3) confirms the significant association of larger subsidy levels and increased system costs, reinforcing the confidence that the identification strategy accounts for potential drivers of system costs. Finally, the association of larger subsidy levels and increased system costs is even stronger when allowing for linear and non-

Table 5: Cost per Watt of output-based systems

	All obs. included		Drop obs. +- 2 weeks	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
Subsidy level	1.499	3.955	0.898	3.934
	(1.860)	(4.156)	(2.023)	(4.555)
N	3,711	3,711	3,426	3,426
1st- stage partial F-stat.	-	288.5	-	240.6

Notes: The outcome variable is cost per Watt of output- based systems. All specifications include fixed effects for the IOU, county, month, installer as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters as well as an indicator for the number of systems a installer has installed before system i. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results reported in Appendix B, Table B1. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

linear time trends of system costs (columns 4 to 6), confirming that the results or not driven by specific assumptions about the evolution of hardware costs of solar systems.

In Table 5 I redo the same analysis for systems receiving output-based subsidies. Including the estimates after dropping applications within two weeks of subsidy step transitions, none of the coefficients are statistically significant, suggesting that larger subsidy levels do not lead to increased costs when customers receive output-based subsidies.

A comparison of systems between ten and 30 kW (i.e. those who could choose between upfront and output-based subsidy types) can inform us whether the association of larger subsidy levels and increased system costs is purely related to the subsidy type or also depends on the customers characteristics. As shown in Appendix A, Table A1 I find no significant association between subsidy levels, subsidy types and systems costs. This result suggests that still the customer's characteristics drive supply-side inefficiencies related to increased costs. I further study how supply-side inefficiencies and second-degree moral hazard depend on the customers characteristics in Section 5.3.

5.2 Subsidy levels and electricity output

Table 6 shows regression results where the outcome is electricity output of output-based systems. The Table is structured as before, that is, I present OLS and 2SLS on the full data set in columns (1) and (2) and redo this sequence on the subset of data excluding applications in the vicinity of two weeks of subsidy level transitions in columns (3) and (4).

The negative coefficients suggest that larger subsidy levels are associated with a decrease of the electricity output per Watt of output-based systems. However, none of the coefficients is significantly different from zero at conventional thresholds ($p = 0.15$ for the 2SLS estimate in column 2). This suggests that direct financial incentives for a high electricity output in combination with higher verification measures for output-based subsidies may i) prevent second-degree moral hazard related to the quality of installation ii) spillover to pricing and thereby limiting second-degree moral hazard related to costs.

5.3 Heterogeneous effects of second-degree moral hazard

In this section, I first exploit the fact that the first two installations of each installer are subject to a mandatory field inspection (Section 5.3.1). Differences in supply-side inefficiencies depending on whether i) subsidies are received by the system-owner or a third-party are studied in Section 5.3.2 and ii) the system is owned by commercial, government non-profit or residential customers are studied in Section 5.3.3.[17]

[17] In line with Pless and van Benthem (2019), the results so far show no qualitative differences when dropping applications within two weeks of subsidy step transition dates, suggesting that customers anticipating such transitions are less of a concern. I therefore continue the analysis with the full sample.

Table 6: Electricity output per Watt of output-based systems

	All obs. included		Drop obs. +- 2 weeks	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)
Subsidy level	-0.004 (0.010)	-0.016 (0.024)	-0.006 (0.011)	-0.031 (0.028)
N	206,517	206,517	189,912	189,912
1st- stage partial F-stat.	-	285.8	-	215.3

Notes: The outcome variable is electricity output per Watt of output-based systems. All specifications include fixed effects for the IOU, county, month, installer as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters as well as the age in years of the system. The 1st stage partial F-statistic for the instrumental variable is derived from first-stage regression results reported in in Appendix B, Table B1. Robust standard errors clustered at the installer level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

5.3.1 Results for the first two installations

In Table 7, I present regression results for specification 2 where I interact the subsidy level with a variable equal to one if the system installed is among the first two systems installed by an installer. The variable thus indicates if the respective system is subject to a mandatory field inspection and therefore increased verification of an installer's work (see Section 3.3). Column (1) presents results on the cost per Watt of upfront systems using OLS and column (2) presents results using 2SLS. I repeat this sequence for the cost of output-based (columns 3 and 4) and for the electricity output of output-based systems (columns 5 and 6).

The coefficients of *First two* in columns (1) and (2) are similar in size and suggest that upfront systems are on average 0.11 USD cheaper ($p = 0.014$) if they are among the first two installed by an installer and therefore subject to mandatory field inspections. Looking at the cost and electricity output per Watt of output-based systems, heterogeneity related to mandatory field inspections is non-existent as neither

Table 7: Mandatory field inspections

	Cost upfront		Cost output-based		Electricity output output-based	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	0.228***	0.245***	1.481	3.895	−0.004	−0.016
	(0.033)	(0.038)	(1.865)	(4.169)	(0.010)	(0.024)
First two = 1	−0.106*	−0.107*	−0.268	−0.285	−0.001	−0.000
	(0.043)	(0.044)	(0.197)	(0.201)	(0.002)	(0.002)
First two = 1 x Subsidy level	0.121	0.122	1.552	2.041	0.008	0.002
	(0.062)	(0.063)	(1.873)	(2.280)	(0.018)	(0.020)
N	136,876	136,876	3,711	3,711	206,517	206,517
1st- stage partial F-stat.	-	26697.7; 49463.8	-	144.7; 171.29	-	149.4; 572.0

Notes: The outcome variable is cost per Watt of upfront systems (columns 1 and 2), cost per Watt of output-based systems (columns 3 and 4) and electricity output per Watt of output-based systems (columns 5 and 6). All specifications include fixed effects for the IOU, county, month, installer as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters as well as an indicator for the number of systems a installer has installed before system i and the age in years of the system in columns 5 and 6. The 1st stage partial F-statistics for both instrumental variables is derived from first- stage regression results, where the second F-statistic is derived from the first-stage of the interacted variable. First-stage results are reported in Appendix B, Table B3. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

the coefficients on *Fist two=1*, nor the interaction terms are statistically significant. As discussed in Section 3.2, output-based systems are subject to higher verification, reducing the potential of mandatory field inspections to change behavior.

5.3.2 Results for subsidy recipients

Table 8 shows regression results for specification 2 where I interact the subsidy level with a variable indicating if a solar system is owned by a third party other than the homeowner. Column (1) presents results on the cost per Watt of upfront systems using OLS and column (2) presents results using 2SLS. This sequence is repeated for the cost of output-based (columns 3 and 4) and for the electricity output of output-based systems (columns 5 and 6).

The significant and positive estimate on *TPO* from column 2 suggest that TPO systems are on average more expensive than HO systems. In addition, the significant interaction term *TPO x Subsidy level* is twice as high as the coefficient of *Subsidy level*, implying that the association of larger subsidy levels and increased costs is much more

Table 8: Third- party owned systems

	Cost upfront		Cost output-based		electricity output output-based	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Subsidy level	0.136^{***}	0.150^{***}	-0.035	3.473	-0.008	-0.027
	(0.034)	(0.040)	(3.581)	(4.415)	(0.011)	(0.019)
TPO = 1	0.161^{***}	0.160^{***}	-0.336	-0.092	-0.000	-0.001
	(0.020)	(0.020)	(0.469)	(0.432)	(0.001)	(0.002)
TPO = 1 x Subsidy level	0.315^{***}	0.307^{***}	1.252	3.804	-0.009	-0.009
	(0.027)	(0.029)	(2.539)	(4.175)	(0.010)	(0.014)
N	136,876	136,876	3,711	3,711	206,517	206,517
1st-stage partial F-stat.	-	26345.8; 1.7e+5	-	240.2; 410.9	-	207.1; 549.4

Notes: The outcome variable is cost per Watt of upfront systems (columns 1 and 2), cost per Watt of output-based systems (columns 3 and 4) and electricity output per Watt of output-based systems (columns 5 and 6). All specifications include fixed effects for the IOU, county, month, installer as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters as well as an indicator for the number of systems a installer has installed before system i and the age in years of the system in columns 5 and 6. The 1st stage partial F-statistics for both instrumental variables is derived from first- stage regression results, where the second F-statistic is derived from the first-stage of the interacted variable. First-stage results are reported in Appendix B, Table B4. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

pronounced for systems owned by a third-party compared to home-owned systems. These results are in line with the previous literature, which has stated that TPO firms may have incentives to increase overall tax credits and therefore inflate the costs and size of systems (Podolefsky, 2013). This trend is confirmed in the analysis of Pless and van Benthem (2019).[18] In combination with milder verification procedures for TPO systems (see Section 3.4), these results suggest that such systems might be particularly prone to supply-side inefficiencies and second-degree moral hazard. Again I do not observe any heterogeneity of cost and electricity output of output-based systems with respect to TPO systems.

[18] A similar analysis in the data, which includes non residential systems, confirms this trend to a certain extent. Replacing the outcome variable in specification 2 with a system's nameplate rating, I find that TPO systems are on average 0.12kW larger, $p = 0.090$.

5.3.3 Results for ownership

Next I turn to an analysis of heterogeneous effects depending on whether customers can be categorized as commercial, government, non-profit or residential. Table 9 shows regression results for specification 2 where I interact the subsidy level with a variable indicating the category of a customer. Commercial customers are employed as the reference category and the coefficient *Subsidy level* therefore has to be interpreted as the association of subsidy levels and costs/ electricity output per Watt for commercial customers. Column (1) presents results on the cost per Watt of upfront systems using OLS and column (2) presents results using 2SLS. I repeat this sequence for the cost of output-based (columns 3 and 4) and for the electricity output of output-based systems (columns 5 and 6).

The significant coefficients of *Government* and *Non-Profit* in columns (1) and (2) show that the cost per Watt of governmental customers is on average approximately one USD larger and the cost per Watt of non-profit customers is on average approximately 0.5 USD lower than that of commercial customers receiving upfront subsidies. Both observations are in line with installers having different valuations for customer types (i.e. with heterogeneity of λ in equation 1). The system costs of governmental customers are ultimately borne by the tax-payer, which may reduce the extent in how far installers care for the customer's benefits λ and thus trigger installers to charge higher prices. Adversely, non-profit organizations are often supported with donations and have less financial resources which may in turn increase λ and result in cheaper systems (see also Borenstein, 2017, who find that smaller and poorer households are charged less for solar systems). Note that the interaction term *Non-Profit x Subsidy level* is positive and statistically significant, suggesting that the reduction in cost is in part outweighed by increased costs when non-profit customers receive larger subsidy levels.

Looking at the 2SLS estimates for output-based systems, I observe no heterogeneity

Table 9: Customer sector

	Cost upfront		Cost output-based		Electricity output output-based	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	0.276**	0.184	2.309	−10.577	−0.003	−0.069
	(0.095)	(0.102)	(2.192)	(16.817)	(0.014)	(0.039)
Sector						
Government	0.845*	1.039**	0.359	1.047	0.001	0.004
	(0.329)	(0.402)	(0.220)	(0.942)	(0.001)	(0.002)
Non-Profit	−0.459***	−0.474***	0.270	0.760	0.002	0.005*
	(0.120)	(0.131)	(0.418)	(0.953)	(0.002)	(0.002)
Residential	0.052	0.042	0.019	0.264	−0.005	−0.004
	(0.058)	(0.056)	(0.499)	(0.678)	(0.003)	(0.003)
Sector x Subsidy level						
Government x Subsidy level	0.144	0.039	−0.160	−1.558	0.005	−0.012
	(0.263)	(0.323)	(1.887)	(2.940)	(0.013)	(0.016)
Non-profit x Subsidy level	0.312*	0.410**	−4.370	−6.884	−0.011	−0.002
	(0.122)	(0.132)	(2.762)	(4.040)	(0.020)	(0.023)
Residential x Subsidy level	−0.065	0.029	−8.115***	−3.698	−0.011	0.019
	(0.083)	(0.086)	(2.258)	(5.780)	(0.017)	(0.024)
N	136,876	136,876	3,711	3,711	206,517	206,517
1st-stage partial F-stat.	-	31145.7; 271.5; 435.5; 1.5e+05	-	62.3; 183.2; 100.3; 2056.5	-	157.6; 171.0; 139.0; 1516.1

Notes: The outcome variable is cost per Watt of upfront systems (columns 1 and 2), cost per Watt of output-based systems (columns 3 and 4) and electricity output per Watt of output-based systems (columns 5 and 6). All specifications include fixed effects for the IOU, county, month, installer as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters as well as an indicator for the number of systems a installer has installed before system i and the age in years of the system in columns 5 and 6. The 1st stage partial F-statistics for the four instrumental variables is derived from first-stage regression results, where the second F-statistic is derived from the first-stage of the interacted variable for government customers, the third F-statistic is derived from the first-stage of the interacted variable for non-profit customers and the fourth F-statistic is derived from the first-stage of the interacted variable for residential customers. First-stage results are reported in Appendix B, Table B5. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

of costs (column 4) but for the electricity output per Watt (column 6). The coefficient of *Non-Profit* is significant and positive, suggesting that solar systems owned by non-profit customers have a better ratio of actually produced electricity per installed Watt than that of commercial customers although this difference is comparably small in size ($p = 0.038$). Again, this result can be attributed to heterogeneity in the valuation of customer benefits and installers may have a higher valuation for the benefits of non-profit customers (i.e. larger λ) when they are perceived as financially less-endowed entities.

6 Discussion and conclusion

In this paper, I studied supply-side inefficiencies and second-degree moral hazard of installers induced by the credence component of energy-transforming technologies. To this end, I analyzed data from a solar subsidy program in California and quantified the relationship of subsidy levels and the cost and electricity output per Watt of solar systems. Employing an instrumental strategy to account for potential self-selection of installers into specific subsidy levels and further controlling for a wide range of potential confounding factors, I find that the cost of upfront solar systems increases if subsidy levels are higher. Further, I do not find robust evidence of supply-side inefficiencies and second-degree moral hazard related to output-based subsidies. Finally, the conclusions are strengthened by the observation that supply-side inefficiencies and second-degree moral hazard i) are reduced when the installer's work is subject to increased verification, ii) are larger for TPO systems and iii) more pronounced for government and less pronounced for non-profit customers compared to commercial customers.

The results provide novel insights for two different kinds of research avenues. First, they contribute to the literature evaluating the cost-effectiveness of environmental subsidy programs and show that such programs need to be robust towards supply-side inefficiencies and second-degree moral hazard of installers induced by the credence component of energy-transforming technologies. My empirical analysis suggests that program administrators should i) account for the cost of second-degree moral hazard induced by upfront subsidies, ii) impose stricter verification measures on the work of installers and iii) should take special care of TPO systems as these seem most prone to supply-side inefficiencies and second-degree moral hazard.

Second, this paper documents that stylized findings from other credence goods markets are relevant for the market of energy-transforming technologies. This paper is the first to document evidence of second-degree moral hazard in the context of energy-transforming technologies. The results further confirm heterogeneity of supply-side inefficiencies depending on who bears their costs (Balafoutas et al., 2013; Gottschalk et al., 2020). It is a promising route for future research to further uncover dimensions of heterogeneity in supply-side inefficiencies and second-degree moral hazard as well as related solutions.

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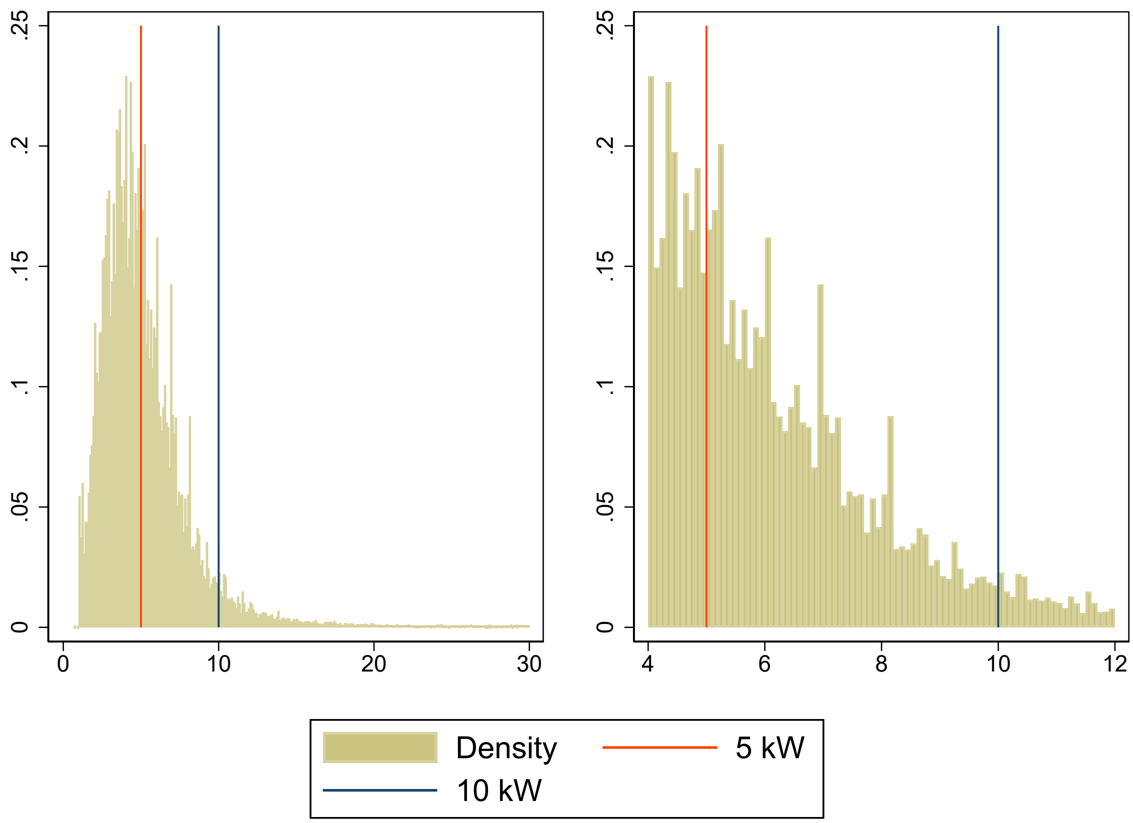
A Within analysis of subsidy types

Figure A1: Size distribution of upfront systems

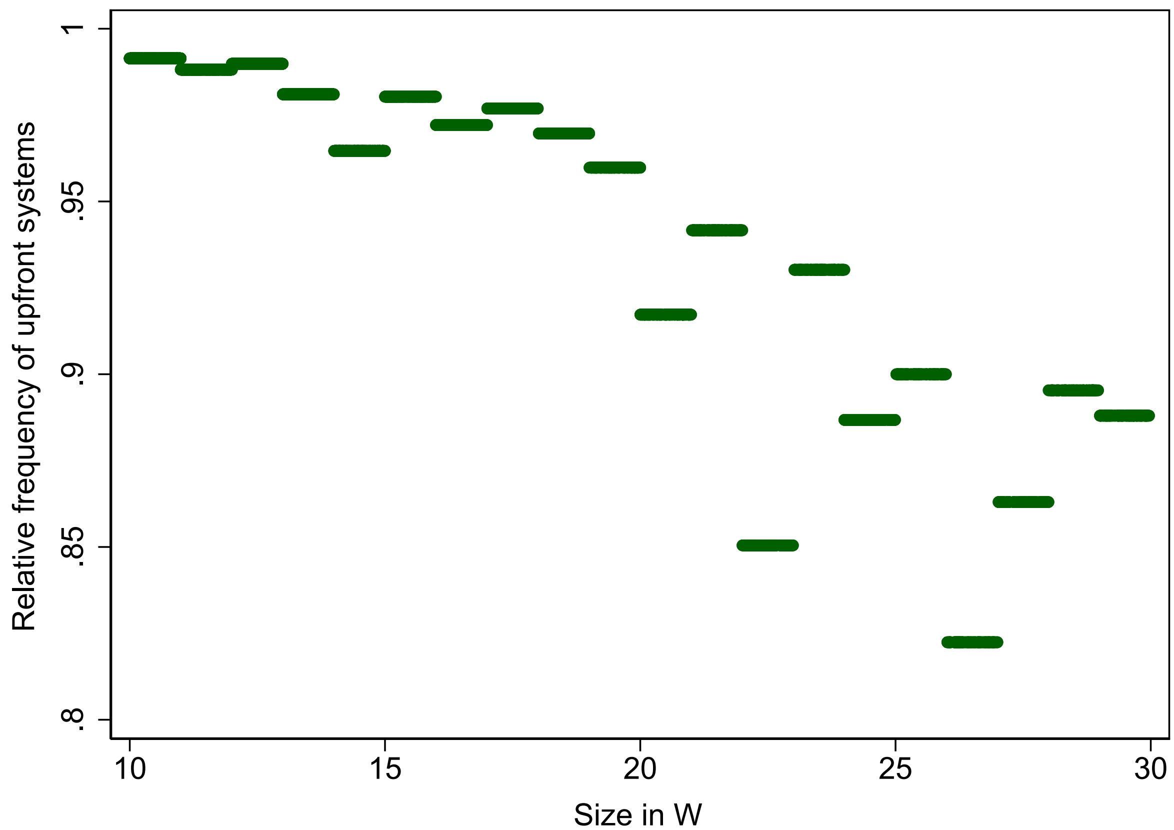


Notes: Distribution of system size of upfront systems. The left panel shows all upfront systems up to 30 kW. The right panel shows the distribution of the subset of system sized four to twelve kW.

Customers installing a system sized between ten and 30 kW could choose to receive upfront or output-based subsidies. As I argue in this paper, the design of output-based subsidies make them more robust to supply-side inefficiencies. Strategic self-selection into either subsidy type could hence bias the results. If for example, installers would want to maximize the upfront amount of subsidies received, one would observe disproportionately many (or a bunching of) upfront systems with a size just below the threshold of 30 kW. Figure A1 shows the distribution of system size of upfront systems. There is no evidence of bunching at 30kW, suggesting that installers do not choose a system size so as to maximize the upfront subsidies received. In line, Figure A2 shows a declining ratio of upfront to output-based systems by system size in the range between ten and 30 kW. The decline of the ratio strengthens the conclusion that the choice on the subsidy type indeed depends on the systems size rather than strategic considerations.

I then turn to analyze whether second-degree moral hazard is related to the subsidy

Figure A2: Ratio of upfront and output-based systems



Notes: Ratio of upfront to output-based systems by size if system size is between 10 and 30 kW. The bin size is 1 W, so for example the first band represents the ratio conditional on systems being sized from 10 to 11W.

type or rather the customer's characteristics. In this section, I only consider systems installed by installers who are not specialized in setting up either upfront or output-based systems, pool these systems and run specification 2 interacting the Subsidy level with a variable equal to one if the system receives upfront subsidies.

Table A1 shows related results where I include systems within ten and 30 kW (i.e. those who could choose the subsidy type) in columns (1) and (2). Given that higher upfront subsidies lead to increased costs (see Section 5.1) installers may want to maximize their gains by installing large upfront systems (see Section 3.2). I therefore analyze large systems which could choose the subsidy type separately and include system of more than 20 (25) kW in columns (3) and (4) (5 and 6).

None of the estimates is significantly different from zero suggesting that the cost per Watt of systems and second-degree moral hazard does not differ by subsidy type. This result suggests that still the customer's characteristics (i.e. having smaller systems and presumably less private information) drive second-degree moral hazard related to increased costs.

Table A1: Within regressions

	10 to 30 kW		20 to 30 kW		25 to 30 kW	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	−1.541	123.483	2.835	35.096	2.104	90.267
	(2.077)	(190.272)	(3.801)	(214.332)	(11.553)	(108.852)
Upfront	0.024	5.391	0.568	0.298	0.207	−0.437
	(0.233)	(8.549)	(0.304)	(1.960)	(2.205)	(5.691)
Upfront x Subsidy level	1.760	−119.385	−2.869	−33.517	−2.420	−85.865
	(2.034)	(184.370)	(3.618)	(203.194)	(10.855)	(103.582)
# Observations	4,999	4,999	586	586	161	161
1st-stage partial F-stat.	-	1487.9; 1455.3	-	359.7; 348.2	-	142.9; 98.3

Notes: The outcome variable is cost per Watt. I pool upfront and output-based systems. All specifications include fixed effects for the IOU, county, month and installers. Note that columns 3 to 6 do not include fixed effects for make and model of modules and inverters because the number of clusters is otherwise insufficient to calculate a robust covariance matrix. Further, I only include installers who install both upfront and output-based systems. I explicitly control for the size of the system. The 1st stage partial F-statistics for both instrumental variables is derived from first-stage regression results, where the second F-statistic is derived from the first-stage of the interacted variable. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

B First stage-regression results

Table B1: First stage results for Tables 3, 5 and 6

	Table 3		Table 5		Table 6	
	All obs. (1)	Dropped obs. (2)	All obs. (3)	Dropped obs. (4)	All obs. (5)	Dropped obs. (6)
Predetermined s_i	0.855^{***}	0.886^{***}	0.415^{***}	0.396^{***}	0.413^{***}	0.393^{***}
	(0.004)	(0.004)	(0.024)	(0.026)	(0.024)	(0.027)
# Observations	136,876	125,038	3,711	3,426	206,517	189,912

Notes: The outcome variable is the subsidy level of upfront systems in columns (1) and (2) and the subsidy level of output-based systems in columns (3) to (6). All specifications include fixed effects for the IOU, county, month of installation, installers as well as make and model of modules and inverters. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

Table B2: First stage results for Table 4

	(1)	(2)	(4)	(5)	(6)
Predetermined s_i	0.855^{***}	0.877^{***}	0.869^{***}	0.872^{***}	0.876^{***}
	(0.004)	(0.023)	(0.004)	(0.004)	(0.004)
# Observations	136,876	136,876	136,876	136,876	136,876

Notes: The outcome variable is the subsidy level of upfront systems in columns (1) and (2) and the subsidy level of output-based systems in columns (3) to (5). All specifications include fixed effects for the IOU, county, month of installation, installers as well as make and model of modules and inverters. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

Table B3: First stage results for Table 7

	Cost upfront		Cost output-based		Electricity output output-based	
	s_i (1)	First Two x s_i (2)	s_i (3)	First Two x s_i (4)	s_i (5)	First Two x s_i (6)
Predetermined s_i	0.854^{***}	-0.007^{***}	0.415^{***}	-0.008^{***}	0.413^{***}	-0.001^{***}
	(0.004)	(0.001)	(0.024)	(0.004)	(0.024)	($0.5e-4$)
# Observations	136,876	136,876	3,711	3,711	206,517	206,517

Notes: The outcome variable is the subsidy level of upfront systems in columns (1) and the subsidy level of output-based systems in columns (3) and (5). In columns (2), (4) and (6) the outcome variable is the respective subsidy level interacted with a variable indicating whether the system is among the first two installed by an installer. All specifications include fixed effects for the IOU, county, month of installation, installers as well as make and model of modules and inverters. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

Table B4: First stage results for Table 8

	Cost upfront		Cost output-based		Electricity output output-based	
	s_i	TPO x s_i	s_i	TPO x s_i	s_i	TPO x s_i
	(1)	(2)	(3)	(4)	(5)	(6)
Predetermined s_i	0.854^{***}	-0.034^{***}	0.473^{***}	-0.208^{***}	0.452^{***}	-0.201^{***}
	(0.004)	(0.002)	(0.022)	(0.021)	(0.022)	(0.019)
# Observations	136,876	136,876	3,711	3,711	206,517	206,517

Notes: The outcome variable is the subsidy level of upfront systems in columns (1) and the subsidy level of output-based systems in columns (3) and (5). In columns (2), (4) and (6) the outcome variable is the respective subsidy level interacted with a variable indicating whether the system owned by a third-party. All specifications include fixed effects for the IOU, county, month of installation, installers as well as make and model of modules and inverters. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

Table B5: First stage results for Table 9

	Cost upfront				Cost output-based				Electricity output output-based			
	s_i (1)	Gov x s_i (2)	Np x s_i (3)	Res x s_i (4)	s_i (5)	Gov x s_i (6)	Np x s_i (7)	Res x s_i (8)	s_i (9)	Gov x s_i (10)	Np x s_i (11)	Res x s_i (12)
Predetermined s_i	0.616*** (0.008)	0.699*** (0.023)	0.781*** (0.012)	0.985*** (0.001)	0.316*** (0.040)	0.611*** (0.023)	0.603*** (0.014)	0.981*** (0.012)	0.411*** (0.028)	0.603*** (0.025)	0.588*** (0.027)	0.977*** (0.013)
# Observations	136,876	136,876	136,876	136,876	3,711	3,711	3,711	3,711	206,517	206,517	206,517	206,517

Notes: The outcome variable is the subsidy level of upfront systems in columns (1) and the subsidy level of output-based systems in columns (5) and (9). In columns (2), (6) and (10) the outcome variable is the respective subsidy level interacted with a variable indicating whether the customer is governmental (Gov). In columns (3), (7) and (11) the outcome variable is the respective subsidy level interacted with a variable indicating whether the customer is non-profit (Np). In columns 4, 8 and 12 the outcome variable is the respective subsidy level interacted with a variable indicating whether the customer is residential (Res). All specifications include fixed effects for the IOU, county, month of installation, installers as well as make and model of modules and inverters. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.