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Abstract

This paper studies how subsidies for photovoltaic solar systems can lead to second-degree moral hazard - the impulse of installers to increase factors determining the total subsidies and/or transaction when consumers receive larger subsidy levels. 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 the expected electricity output and transaction prices of PV systems in California. The results are consistent with hypothesized drivers of second-degree moral hazard as larger subsidy levels are associated with i) an increased measure of the expected electricity output leading to increased subsidies when third-parties own the PV system and ii) increased transaction prices when consumers themselves own the system. The results further suggest that subsidy programs should verify the work of an installer, for example during mandatory field inspections, as these reduce second-degree moral hazard.

Keywords: PV 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 such as photovoltaic solar (PV) systems. 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 some characteristics of PV systems are subject to informational asymmetries typical for credence goods. In particular, installing PV systems consists of a complex arrangement of different technological components and working steps (Giraudet et al., 2018; Gillingham et al., 2016) which many consumers deliberately leave to professional installers. Moreover, consumers face difficulties in verifying 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).

Therefore, professional installers may have incentives to exploit their informational advantage, leading to supply-side inefficiencies typical for credence goods, including overcharging for services or technological components (Giraudet et al., 2018; Giraudet, 2020; Lanz and Reins, 2021). The literature on credence goods further 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 transaction price paid by consumers, installers may be *more* inclined to increase the transaction price of PV systems (Kerschbamer et al., 2016; Huck et al., 2016;

[1] In the context of energy-transforming technologies such as PV systems, first-degree (or demand-side moral hazard) implies that consumers install PV 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).

Balafoutas et al., 2017, 2020). In addition, when the total amount of subsidies received is determined by self-reported values on system characteristics, installers may have incentives to exaggerate such values in order to increase the overall amount of subsidies received.

In this paper I study how subsidies may trigger second-degree moral hazard and hence i) increase the total amount of subsidies received and ii) increase transaction prices of PV 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 and related data on subsidized PV systems make the program particularly relevant for this research. First, the CSI offers regional and chronological variation of subsidies enabling the identification as to how the expected electricity output as measured by the design factor of a system and transaction prices depend on the magnitude of received subsidies. Specifically, the CSI provides subsidies to consumers 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 PV systems. The subsidy level available to consumers 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.

Second, to calculate the total amount of subsidies a consumer receives, the CSI program uses self-reported data on expected electricity output (or hereafter the design factor) of a system. In particular, consumers have to report specific system characteristics, such as its location, shading, orientation as well as the make and model of installed PV modules and inverters. However, only a fraction of PV systems is subject to a mandatory field inspection where the accuracy of these characteristics is verified. Increased verification is a well studied countermeasure to supply-side inefficiencies in markets for credence goods and I can identify systems where the applicant knew that the system characteristics were verified during a field inspection by the CSI, allowing me to assess how such verification affects second-degree moral hazard.

In the empirical analysis, I quantify the impact of subsidy levels on the design factor and transaction prices, 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 market power, ii) month of installation FE to capture national demand shocks and general time trends for hardware prices, iii) regional FE to capture local 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 further 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 PV 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 design factor and transaction prices 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 design factor and/or transaction prices of systems.

I study heterogeneity of supply-side inefficiencies along three dimensions that have been highlighted as important factors driving second-degree moral hazard (see Balafoutas et al., 2017, for a related discussion). As a first dimension, I study whether second-degree moral hazard is increased if a system is third-party owned (TPO) and hence the installers directly receives the subsidy as opposed to home-owned (HO) systems where the consumer receives the subsidy. As a second dimension, I study increased verification of installations and their potential to prevent second-degree moral hazard (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 PV systems installed by each installer. Finally, I study how second-degree moral hazard depends on whether a system is owned by a commercial, residential, non-profit or governmental consumer.

The empirical analysis shows evidence suggesting that second-degree moral hazard is highly relevant in the context of upfront subsidies. First, I find that a one dollar increase of upfront subsidies is associated with a statistically significant 0.5 percentage points increase of the design factor of residential TPO systems. Such an increase is for example equivalent to reporting a five degree difference in the module tilt toward the optimal tilt. When systems are subject to a mandatory field inspection, there is no statistically significant association, suggesting that increased verification prevents installers from reporting exaggerated system characteristics. I do not find any significant marginal effect of the subsidy level on the design factor of HO systems.

Concerning transaction prices, I do find a significant marginal effect of the subsidy level of HO systems for all consumer sectors, suggesting that a one dollar increase of the subsidy level increases the transaction prices by 3.5 to 7.5 percent at the mean subsidy level. For TPO systems, I only find such an effect for governmental consumers. This effect is however very large as a one dollar increase of the subsidy level is associated with a 25 to 50 percent increase of the transaction price per Watt at the mean of our sample. Overall, these results are in line with a business strategy to increase the short-term cash flow of installers, because TPO installers receive the total subsidies and HO installers receive the transaction price directly after the installation .

These findings contribute to three different kinds of research avenues. First, Davidson and Steinberg (2013) and Podolefsky (2013) have documented that some TPO installers inflate the transaction price of residential PV systems to reap larger tax credits. Yet, Pless and van Benthem (2019) somewhat surprisingly find that pass through of residential TPO systems receiving upfront subsidies is higher and attribute this effect to imperfect competition on the market for TPO systems in combination with a sufficiently convex demand curve. The results in this paper suggest that TPO installers do increase the total amount of subsidies received and at the same time, do not adjust the transaction prices. Therefore, second-degree moral hazard provides a parallel explanation for the over-shifting of subsidies found in Pless and van Benthem (2019) as TPO installers do not increase transaction prices after increasing the total amount of subsidies received. Potentially, competitive pressure in TPO markets may drive installers to increase cash-flow by inflating short-term payments via larger subsidy transfers and then acquire more new consumers with lower transaction prices.

Second, results from the literature assessing the optimal subsidy design to increase adoption and cost-effectiveness of subsidy programs show that consumers significantly discount future subsidy payments and that upfront subsidies are a cheaper way to foster the adoption of PV systems than feed-in 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 the final amount of upfront subsidies received should not be based on self-reported data on the expected electricity output of a system, unless this data is verified.

Finally, this paper substantiates that stylized findings from other credence goods markets are relevant for the market of energy-transforming technologies (Giraudet, 2020; Lanz and Reins, 2021). My analysis 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 limit second-degree moral hazard related to increased total subsidies and also transaction prices. The results in this paper further confirm heterogeneity of supply-side inefficiencies depending on who bears their costs (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 design factor as well as transaction prices of PV 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 PV systems, supply-side inefficiencies and second-degree moral hazard

I illustrate the implications of the credence nature of PV systems in the context of the CSI program building on the framework of Dulleck and Kerschbamer (2006). I assume that there are two types of PV systems: those with high quality technological components q_h and those with lower quality technological components q_l. The electricity output of system i, $Vi(q_i, l_i, d_i)$ is increasing in the quality of technology, the quality of labor exerted during the installation l_i and the systems design factor d_i. The design factor is a measure of the system's real world potential for electricity output accounting for the system's technological components, its mounting method, orientation, tilt, azimuth, and shading as well as the solar irradiation at its location.

The installer faces a cost for installing a system which increases in both, the cost of technology and the cost for labor (i.e. $c_i(q_i, l_i)$). Then consumers pay the transaction price for the system which is increasing in labor and hardware costs $p_i(c_i)$. The installer's benefit from putting up a PV system hence equals the difference of the transaction price and costs of provided hardware and labor $\pi_{installer} = p_i(c_i) - c_i(q_i, l_i)$. The consumer's benefits from investing in a PV system can be expressed as $\pi_{consumer} = V_i(q_i, l_i, d_i) - p_i(c_i) + s_i$. In this equation, p_i is the (pre-incentive) transaction price determining the amount of money the installer receives for setting up the system and $p_i - s_i$ is the post incentive price determining what the consumer actually pays to set up his system accounting for the received subsidies.

The credence nature of PV systems implies that there is asymmetric information on q_i, l_i and d_i (see Giraudet et al., 2018, for a similar assumption). In particular, there is a significant cost to verify whether the self-reported information on the design factor is correct, which technology was installed and whether the technology was mounted and wired in an appropriate way. This implies that an installer has some margin with respect to determining the design factor and also transaction prices. If an installer knows that his work will not be verified and if he only cares about his own profits, he has the incentive to increase transaction prices. Such behavior can be expressed with $\sigma \in [0, 1]$ where $\sigma = 1$ indicates exploiting asymmetric information to a maximum leading to maximized total subsidies and transaction prices while $\sigma = 0$ is equivalent to the fair transaction price if there was no asymmetric information.

Next, evidence in markets for credence goods suggests that increased verification measures imposed to detect and punish 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. The CSI program administrators demand that the first two systems installed by each installer are subject to mandatory field inspections where the system's characteristics and functionality are verified. Such mandatory field inspections increase verifiability of the installers' work and allow me to estimate their effect on the design factor and transaction prices.

Moreover, it has been shown that agents in markets for credence goods care for the consumer'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 PV systems, it seems plausible that a large heterogeneity in λ exists, implying that many installers care for the consumer's benefits and therefore provide flawless services (see for example Kerschbamer et al., 2017). At the same time, differences in the consumer 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 consumers 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 consumers (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:

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

The literature on credence goods further suggests that an installer may alter his behavior conditional on the magnitude of the subsidy the consumer receives. In particular, second-degree moral hazard in the context of PV systems implies that installers *further* increase the transaction prices of PV systems when consumers receive larger subsidies.

Importantly, the CSI program is designed such that the total amount of upfront subsidies is increasing in the design factor of systems $s_i(d_i)$ which is multiplied with the subsidy level and the system size to determine the total amount of the upfront subsidy. Second-degree moral hazard may therefore imply that installers also increase the design factor of systems to maximize the total amount of subsidies received.

3 The California Solar Initiative program

The California Solar Initiative (CSI) program provides a useful setup where predetermined subsidy levels are assigned to different consumers, enabling me to analyze the associated relation with the design factor and transaction prices of PV systems. This section starts with a general description of the program. Afterwards, I describe which features of the CSI are exploited to study second-degree moral hazard related to the subsidy recipient, increased measures of verification and differences in system ownership. Finally, I describe the main outcome variables of the empirical section: the design factor and the transaction price.

3.1 Program description

The CSI subsidy program was rolled out in 2007 using a budget of $2.167 million for the goal to install 1940 mW within 10 years. All consumer sectors could apply for the program including residential, commercial, government and non-profit consumers. The subsidy studied in this paper ("*Expected Performance Based Buyout", or EPBB*) is intended for residential and small business consumers installing a system with less than 30 kW and takes the form of a one time lumpsum payment. The size of the lumpsum payment is determined by multiplying the subsidy level with the design factor and system size.

The subsidy level available to consumers is determined by the cumulative capacity of already installed systems within the IOU of the consumer. Once a certain threshold of cumulative mW in an IOU is passed, the subsidy level decreases. In particular, the CSI provides subsidies to consumers 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 and time. One can see that for example in January 2010, many different upfront subsidy levels were attributed to different PV systems in all IOUs. Contrasting the unique subsidy levels in each mW step, some systems receive weighted averages of up to four

Table 1: CSI subsidy levels

mW Step	mW in step	Residential/ Commercial	Gov't/ Nonprofit
1	50	n/a	n/a
2	70	2.5	3.25
3	100	2.2	2.95
4	130	1.9	2.65
5	160	1.55	2.3
6	190	1.1	1.85
7	215	0.65	1.4
8	250	0.35	1.1
9	285	0.25	0.9
10	350	0.2	0.7

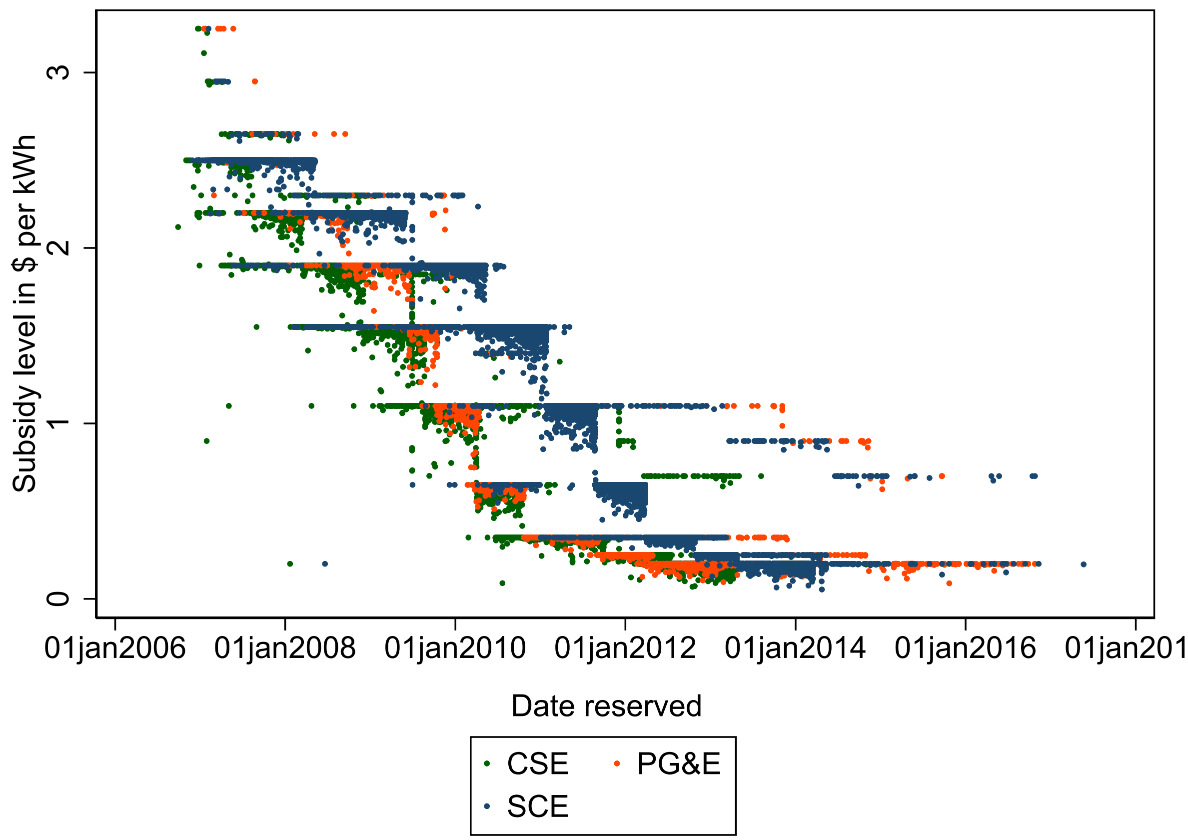
Notes: Subsidy levels in $ per Watt. Extract from Table 4 of California Public Utilities Commision (2017).

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 a later point in time receive a higher subsidy rate.[2]

While the subsidy levels attributed to systems are predetermined by the mW step, the total subsidy amount is increasing in the system size. Accordingly, installers can further increase the total subsidy amount a consumer receives by installing larger systems. To avoid the installation of unreasonably sized systems the CSI imposed rather strict limitations to substantiate a system's size and to ensure that a system is sized such that it optimally serves the consumer's 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 the last twelve months. Second, no applicant may receive a total amount of subsidies that exceeds the transaction price of the system. Third, there is a cost cap for applications implying that the transaction price per Watt may not be larger than the 12 month rolling average of the transaction price per Watt of other systems plus one dollar.

[2] 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 liberated capacity under a subsidy step which was already exhausted or an adjustment of CSI subsidies if systems receive other benefits (Hughes and Podolefsky, 2015).

Figure 1: Evolution of subsidy levels



Notes: Subsidy levels over time and IOU's.

Studying the distribution of systems around two arbitrary thresholds provides information on whether installers strategically influence the size of systems. First, systems smaller than five kW were not required to submit 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.[3] Figure A1 in Appendix A presents the size distribution of PV systems in the range between zero and 30 kW in the upper panel, between four and six kW in the lower left panel and between nine and eleven kW in the lower right panel. There are not disproportionately many systems sized just below five or ten kW, affirming that the system size is determined by the consumer's needs rather than strategic considerations (see also Gillingham et al., 2016; Pless and van Benthem, 2019, for similar conclusions on the sizing of PV systems).

3.2 Subsidy recipients

Instead of buying a PV system, CSI consumers can choose to lease a PV system from a third party (Podolefsky, 2013; Pless and van Benthem, 2019).[4] In this case, TPO installers pay the installation costs and receive the final subsidy (i.e. they directly receive s_i Equation 2).

The US treasury department has investigated the pricing of some TPO installers, as these were accused of increasing fair-market values in order to reap larger tax credits

[3] For other system sizes the application fee equals 1250 USD for systems up to 30kW. Note that this fee is refunded once the system is installed.

[4] If consumer 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 consumer pays a monthly leasing rate to the third party and owns the electricity output. In a PPA contract, the consumer pays a 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 consumer 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.

(Trabish, 2013). Because TPO installers finance the upfront installation costs and the transaction price to installers is paid in form of dispersed leasing rates, TPO installers may have incentives to increase short-term cash flows in order to increase their market value (Salzman, 2013). As the CSI subsidies are paid directly after the installation of a system, TPO installers can increase their short-term cash flow by increasing the total amount of subsidies received. As discussed by Pless and van Benthem (2019), such a business strategy may affect estimates of subsidy pass-through, because inflated total subsidies would artificially decrease the post incentive price and therefore falsely be attributed to a larger pass-through.

3.3 Increased verification

Following the CSI rules, the first two PV 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 to calculate the design factor.[5] In particular, mandatory field inspections thus 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 PV system and its installer can be dismissed from the program.

This rule is public knowledge and thus known by installers. Mandatory field inspection increase the probability γ of detecting supply-side inefficiencies and installers face commercial consequences after detection (i.e. $t > 0$). In turn installers may limit

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

exaggerating the design factor and/or increasing transaction prices 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 prices and supply-side inefficiencies are specifically pronounced in domains defined as *hard to observe*).

3.4 Sector of consumer

Furthermore, installers in the sample face commercial, residential, non-profit and governmental consumers. This enables me to study differences behind the entities owning PV 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 transaction prices when consumers are perceived as wealthier and the financial consequences are borne by an anonymous entity compared to a residential consumer 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 consumer (Kandul et al., 2020). If installers perceive non-profit and residential consumers as less financially endowed and therefore have a higher valuation for their benefits (i.e. a larger λ) compared to commercial and government consumers, one would expect to observe differences in second-degree moral hazard depending on the consumer sector.

3.5 Measures of the design factor and transaction price

To document second-degree moral hazard in the context of PV systems this paper analyses the design factor and transaction prices of PV systems under different subsidy levels. The design factor is calculated by the CSI, based on the following criteria reported by the PV system's applicant: the zip code and IOU of the installation location, the sector of the applicant, the make, model and number of PV modules and inverters, the mounting method, the tilt and azimuth of the PV system and the shading of the system including a precise measure if there is shading. The CSI then calculates the expected production of the proposed system based on the reported characteristics and compares it to a reference system. In particular, this comparison includes i) a design correction to account for differences in tilt and azimuth, ii) a geographic correction to account for differences in the location with respect to temperature and solar irradiation at the respective zip code, and iii) an installation correction to account for differences in the mounting method relative to laboratory test conditions. While the zip code as well as make, model and number of technological components may be easier to verify and applicants would therefore need to deliberately misreport in order to increase the design factor, applicants may exploit the asymmetric information and report exaggerated measures of features which are hard to observe, such as a system's shading, tilt and azimuth.

The transaction price of PV systems is the second outcome variable of interest. In line with technical conventions it is divided by the system size. In particular, the system's nameplate rating is used to determine the transaction price per Watt as this measure reflects the system's electricity generating potential under test conditions (see Podolefsky, 2013; Hughes and Podolefsky, 2015; Dong et al., 2018; Pless and van Benthem, 2019, for a similar procedure).[6] The CSI data provides the transaction price for each system, which includes costs for the technological components, construction and installation costs, engineering and design costs, interconnection cost as well as

[6] 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 accounts for differences at the respective 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.

warranty and maintenance costs.[7] 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.

Importantly, earlier literature has assessed the transaction price of HO systems as a reliable measure of what a consumer pays to the installer before subsidies. For TPO systems however, this measure has been deemed inconsistent because the actual transaction price depends on the explicit contract details such as monthly payments, term lengths and upfront payments (Pless and van Benthem, 2019). I therefore conduct the analysis of transaction prices per Watt of HO and TPO systems separately (see Section 5.2). I decide to keep the transaction prices of TPO systems as a benchmark for comparisons and make a disclaimer that all qualitative and quantitative conclusions related to the transaction prices of TPO systems are indicative.

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.

[7] All systems in the sample are eligible to receive investment tax credits (ITC). These take the form of a 30 percent tax credit on the transaction price which was granted to all PV systems installed in the US from 2006-2019. Adjusting the transaction price for the ITC is akin to a linear transformation of the variable, as all systems installed during the sample period receive the same tax credit. Consequently, this procedure would not affect the results. See Pless and van Benthem (2019) for further information.

4.1 Data summary

The information on the applicants of each PV 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).[8]

Table 2: Summary statistics

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean subsidy level ($/W)	2.40	2.02	1.58	1.02	0.59	0.30	0.21	0.20	0.21	0.21
Min subsidy level ($/W)	0.90	0.20	0.65	0.09	0.21	0.07	0.06	0.05	0.09	0.15
Max subsidy level ($/W)	3.25	2.65	2.30	2.30	1.55	1.10	1.10	0.90	0.70	0.70
Mean price per Watt ($/W) (HO)	8.2	8.1	7.8	7.1	6.8	5.5	4.7	4.6	4.2	4.0
Mean price per Watt ($/W) (TPO)	8.2	9.8	7.7	7.1	6.4	5.4	5.0	4.5	4.7	4.9
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	31	27	25	24	25	26	29	29
Mean number of inverters	1	2	3	4	5	6	8	9	11	10
Mean design factor (in pct.)	94.48	94.04	94.46	94.28	94.67	94.29	94.48	95.04	94.73	95.99
Commercial (1,943)	2.8	2.8	1.8	1.8	1.0	0.8	0.8	2.3	4.4	10.6
Government (374)	0.6	0.5	1.1	0.4	0.8	0.0	0.0	0.1	.	0.6
Non-profit (565)	1.1	0.7	0.4	0.5	0.3	0.2	0.2	0.9	3.2	2.5
Residential (135,768)	95.5	96.0	96.6	97.3	98.6	98.9	98.9	96.7	92.3	86.2
Observations (138,650)	6477	9701	13344	18994	21692	31691	30416	5677	498	160
Observations (HO, 70,914)	6019	8308	11429	13120	10179	8918	10134	2407	297	103
Observations (TPO, 67,736)	458	1393	1915	5874	11513	22773	20282	3270	201	57

Notes: Summary statistics for 2006 and 2017 are not reported because there were only 81 applications in these years.

The first three rows show the mean, minimum and maximum subsidy level in a given year. In line with Figure 1, subsidy levels vary considerably within each year. The next two rows show the average transaction price per Watt, for HO and TPO systems separately because of potentially inconsistent values for TPO systems (see Section 3.5 for further details). Importantly, the transaction price per Watt is declining over time for both HO and TPO systems. 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 transaction price and design factor of PV systems is crucial when estimating second-degree moral hazard.

[8] Note that I drop PV systems which have not been installed at the time of the data access. Also, systems without entries for the subsidy level, transaction price or date of reservation were dropped in the data.

Next, the size in kW and the number of modules installed show no specific time trend. The number of modules installed per Watt is decreasing which 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. Also, the total number of inverters installed is increasing over time. Solar inverters are the primary cost drivers of a PV system and their hardware costs have significantly decreased over the sample period. In combination with the observation that the ratio of inverters per module installed also increased, this suggests that early adopters of PV technology limited the installation of installers to cap hardware costs.

The design factor stays constant over the sample period, indicating that neither *low-hanging fruits* with a particular large design factor, nor systems with a particularly bad potential to generate electricity output entered the CSI program early. The next four rows show the distribution of the consumer sector. The systems installed in our sample are predominantly owned by residential consumers, followed by commercial, non-profit and government consumers which is in line with the intended allocation of EPBB to smaller and residential consumers. Finally, one can further observe a strong growth of TPO systems during the sample period.

4.2 Identification strategy

To estimate the association of subsidy levels and the design factor and transaction prices per Watt, I employ regression specifications adapted from Pless and van Benthem (2019). When the outcome variable is the design factor, the regression specification can be written as follows:

$$Y_i = \alpha + \beta_i s_i + X_i \phi + \varphi_u + \varsigma_f + \chi_s + \omega_c + \mu_t + \epsilon_i \quad (1)$$

where Y_i denotes the design factor of system i, and s_i denotes the subsidy level of system i. In addition, I account for entered system characteristics used to calculate the design factor by controlling for the number of modules and inverters $X_i\phi$ and further employing IOU fixed effects φ_u, technology fixed effects ς_f indicating the make and model f of modules and inverters installed in system i to control for quality differences, and sector fixed effects χ_s to control for differences in subsidy levels in the respective sector (see Table 1).

I also make use of installer fixed effects ω_c to eliminate potential bias at the installer level such as measurement errors of the system characteristics. Further, I employ μ_t which is a dummy variable for the month t in which system i was installed to control for the development of the design factor over time. This is important because one could argue that consumers 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 consumers profitable (see Globus-Harris, 2020; Gilbert et al., 2019, for a related discussion of additionality effects). The inclusion of monthly fixed effects prevents me from misinterpreting the association of subsidy levels and the design factor as second-degree moral hazard when it can be actually attributed of additionality. Finally, ϵ_i denotes a random error term and standard errors are clustered at the zip code level to correct for potential correlation of data errors within regional CSI offices (Podolefsky, 2013; Pless and van Benthem, 2019).

When the outcome variable Y_i is the transaction price per Watt, I additionally create variables to control for aspects of the market structure affecting the supply for PV systems. To this end, the control vector $X_i\phi$ includes the rank of the respective installer in terms of total installations within the zip code at month t to control for the development of market power with time (Dong et al., 2018), a measure of the experience of the installer calculated by how many systems an installer installed previous to system i (see Bollinger and Gillingham, 2019, for a discussion of the effects of learning by doing) and the zip code level Herfindahl-Hirschmann Index (HHI) using the share of cumulative installations in a zip code by the installer in the respective year to control for local industry concentration and competition (Gillingham et al., 2016).

I furthermore include the same FE as described above when the outcome variable is transaction price per Watt. In particular, using installer FE in this context is important to address unobserved differences at the installer level, such as increased market power due to more successful marketing campaigns or increased bargaining power when negotiating transaction prices with the consumer and/or lower prices for technology input with the manufacturer.

There is, however, a potential issue with specification 1 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 able 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 design factor and transaction price per Watt of systems only through the subsidy level. It is highly unlikely that installers had such influential market power to influence the total capacity installed within an IOU, preventing them from influencing the transition process from one subsidy level step to another. In addition, it is unclear what incentives such installers would have to shift the capacity level above thresholds or alternatively postpone installations. 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 design factor and transaction price 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:

$$Z_i = \textit{predetermined } s_i \tag{2}$$

Consequently, the first stage regression can be written as:

$$s_i = \eta + \theta Z_i + X_i\tau + \vartheta_u + \varrho_f + \iota_s + \xi_c + \kappa_t + \nu_i. \tag{3}$$

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 design factor and transaction prices per Watt, I interpret β as the causal relation between a one dollar subsidy increase and associated changes of the design factor and transaction prices per Watt of PV systems.

I then study whether the association between subsidy levels and design factor/ transaction price per Watt is affected by increased verification of the installer's work and the ownership of systems. For this purpose, I interact the subsidy level s_i in specification 1 with a variable indicating whether i) a system is subject to a mandatory field inspection, and ii) the system is owned by a commercial, government, non-profit or residential consumer. 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 the design factor/ transaction prices per Watt at the mean subsidy level of the sample.

I complement this identification with a set of robustness checks. Hughes and Podolefsky (2015) as well as Pless and van Benthem (2019) note that consumers 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.[9]

[9] The possibility that consumers 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.

Table 3: Design factor of TPO systems

	All obs. included					
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	0.359^{*}	0.471^{**}	0.360^{*}	0.471^{**}	0.707	1.315
	(0.144)	(0.164)	(0.144)	(0.164)	(0.776)	(0.714)
Field inspection (FI)						
FI = 1 × Subsidy level			−0.602	−0.421		
			(0.445)	(0.467)		
FI = 1			0.708	0.690		
			(0.423)	(0.422)		
Sector						
Government × Subsidy level					−1.086	−2.034
					(2.228)	(3.103)
Non-Profit × Subsidy level					0.795	1.324
					(0.939)	(1.388)
Residential × Subsidy level					0.360^{*}	0.470^{**}
					(0.144)	(0.164)
Government					1.696	2.383
					(1.864)	(2.356)
Non-Profit					0.818	0.825
					(0.730)	(0.755)
Residential					-1.497^{***}	-1.548^{***}
					(0.434)	(0.433)
N	67,230	67,230	67,230	67,230	67,230	67,230
1st-stage partial F-stat.	-	71982.4	-	47312.9; 10032.1	-	319.4; 32.4; 19.6; 24239.2

Notes: The outcome variable is the design factor of TPO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters. 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.

5 Empirical results

I start this section by presenting the impact of subsidy levels on the PV system's design factor (Section 5.1) followed by transaction prices per Watt (Section 5.2). I further analyze implications from the framework in Section 2 and study heterogeneity related to increased verification measures and the ownership of PV systems.

5.1 Subsidy levels and the design factor of upfront systems

Table 3 shows regression results for Equation 1 when the outcome is the design factor of TPO upfront systems and all observations are included.[10] In column (1), I report OLS estimates and in column (2), I report 2-stage least squares (2SLS) estimates where the actually received subsidy level is instrumented with the predetermined subsidy level as shown in equation 2. In columns (3) and (4) I repeat this sequence and interact the subsidy level with a variable equal to one if the system is subject to a mandatory field inspection. In columns (5) and (6) I interact the subsidy level with a variable indicating the sector of the consumer. Table C1 in Appendix C, shows regression results for the same sequence dropping observations in the vicinity of a subsidy level drop date.

In columns (1), and (2) the coefficient on *Subsidy level* is positive and statistically significant. When interacting the subsidy level with a variable indicating whether the system is subject to a mandatory field inspection (*FI = 1*) in columns (3) and (4) the positive association of subsidy levels and the design factor of systems which are not subject to a mandatory field inspection (*Subsidy level*) is similar in size and significance. At the same time, there is no statistically significant association of subsidy levels and the design factor when systems are subject to a mandatory field inspection (*FI = 1 x Subsidy level*). Looking at the marginal effect of the subsidy level by consumer sector in columns (5) and (6), we observe that only residential consumers show statistically significant and positive coefficients which are again similar in size to the coefficients without interaction. Further, residential systems are associated with a statistically significant lower design factor of approximately 1.5 percentage points.

The estimates after dropping observations in the vicinity of a rebate level drop date

[10] 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.

in Table C1, Appendix C are very similar in size and significance, suggesting that the presence of consumers anticipating such dates does not affect the association of subsidy levels and the design factor. Furthermore, the OLS and IV estimates are similar in size, although the IV estimates tend to be larger. A negative endogeneity bias suggests that any omitted variable influencing both the subsidy level and the error term lowers the association between subsidy levels and the design factor. This indicates that the received subsidy levels were not influenced by factors also increasing the design factor (such as for example second-degree moral hazard). Using the predetermined subsidy level as an instrument for the actually received subsidy level further has significant explanatory power indicated by large first-stage F-statistics.

The results show that a one dollar increase of the upfront subsidy is associated with an increase of the design factor of approximately 0.47 percentage points (in my preferred specification in column 2). Following sample calculations of the design factor, an increase of 0.47 percentage points is equivalent to an optimization of the module tilt of 5 degrees.[11] In combination with the observation that there is no such association when systems are subject to a mandatory field inspection where the inputs to calculate the design factor are verified, I interpret these results as evidence that TPO installers do respond to larger subsidy levels and increase the design factor of systems, unless their input is verified during mandatory field inspections.

The positive association between subsidy levels and the design factor for residential consumers is further in line with heterogeneous social preferences depending on the consumer sector as argued in section 2. Inflating and shifting the total amount of subsidies to consumers has the consequence that consumers pay less for their systems. Lower design factors of residential consumers can further potentially be attributed to different intentions to invest in a PV system. Investments by residential consumers

[11] See http://www.csi-epbb.com/ for further information and sample calculations.

Table 4: Design factor of HO systems

	All obs. included					
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	0.010	−0.067	0.006	−0.071	−0.015	−0.135
	(0.105)	(0.122)	(0.105)	(0.122)	(0.206)	(0.255)
Field inspection (FI)						
FI = 1 × Subsidy level			0.117	0.074		
			(0.163)	(0.176)		
FI = 1			−0.410**	−0.434**		
			(0.145)	(0.149)		
Sector						
Government × Subsidy level					−0.084	−0.436
					(0.549)	(0.662)
Non-Profit × Subsidy level					−0.451	−0.467
					(0.307)	(0.348)
Residential × Subsidy level					0.005	−0.064
					(0.105)	(0.121)
Government					−0.551	−0.208
					(0.704)	(0.849)
Non-Profit					0.623	0.617
					(0.383)	(0.421)
Residential					−0.923***	−0.913***
					(0.145)	(0.145)
N	69,113	69,113	69,113	69,113	69,113	69,113
1st-stage partial F-stat.	-	43892.7	-	88043.9; 34064.67	-	3090.8; 296.7; 1018.9; 1.2e+5

Notes: The outcome variable is the design factor of HO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters. 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.

may be motived by an environmental perspective, which implies that the investments are conducted although the location of their system may not be optimal to generate electricity output and therefore have a lower design factor, such as carport structures. Instead, commercial consumers may only want to invest if the location of the system has high potential for large electricity output.

Next, Table 4 shows regression results for Equation 1 when the outcome is the design factor of HO upfront systems. The columns are arranged in the same way as in Table 3. Table C1 in Appendix C, shows regression results for the same sequence dropping observations in the vicinity of a subsidy level drop date.

While there is no statistically significant association of subsidy levels and the design factor, mandatory field inspections are associated with a significant decrease of the design factor of 0.43 percentage points and the design factor of residential systems is approximately 0.9 percentage lower compared to commercial systems. The estimates after dropping observations in vicinity of a subsidy level drop date shown in Table C1, Appendix C are similar in size and significance.

These results suggest that HO systems do not have an increased design factor when they receive larger subsidy levels. The observation that HO systems subject to a mandatory field inspection are associated with a significantly lower design factor suggests that increased verification may trigger conservative reports of system characteristics, as any discrepancies are more likely to be detected. Furthermore, residential consumers are again associated with a lower design factor indicating that residential consumers install PV systems in areas with lower potential to generate electricity output.

Overall, these results suggest that TPO installers increase the design factor of PV systems when they receive higher subsidy levels. This association indicates second-degree moral hazard which, however, does not come at the expense of the consumer but at that of the CSI as the subsidy provider. Because TPO installers receive the total amount of subsidies directly after the installation has been completed and the transaction price paid by the consumer is paid dispersed over time, increasing the amount of subsidies can increase the short-term cash flow. Instead, installers of HO systems receive the full transaction price and they do not receive the subsidies as they are directed to the consumer. Increasing short-term cash flow for HO installations would hence lead to larger transaction prices, which I study in the next section.

Table 5: Transaction price per Watt of TPO systems

	All obs. included					
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	0.045	0.001	0.045	0.001	−0.075	−0.218
	(0.031)	(0.030)	(0.031)	(0.030)	(0.173)	(0.206)
Field inspection (FI)						
FI = 1 × Subsidy level			0.059	0.006		
			(0.149)	(0.150)		
FI = 1			−0.094	−0.091		
			(0.109)	(0.109)		
Sector						
Government × Subsidy level					2.477**	2.358*
					(0.937)	(0.945)
Non-Profit × Subsidy level					0.208	0.297
					(0.277)	(0.490)
Residential × Subsidy level					0.042	0.002
					(0.031)	(0.030)
Government					−0.243	−0.213
					(0.542)	(0.620)
Non-Profit					0.203	0.223
					(0.212)	(0.223)
Residential					0.243*	0.254*
					(0.120)	(0.121)
N	67,230	67,230	67,230	67,230	67,230	67,230
1st-stage partial F-stat.	-	72154.6	-	47481.7; 9919.2	-	313.2; 33.0; 19.59; 24436.8

Notes: The outcome variable is the transaction price per Watt of TPO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters, the experience of installers, the relative market power of installers and a measure for local industry concentration. The 1st stage partial F-statistics for the instrumental variables are 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.

5.2 Subsidy levels and transaction prices per Watt of PV systems

In this section, I study the association of subsidy levels and transaction prices per Watt of PV systems and how it depends on increased verification and the consumer sector. I first analyze the transaction price of TPO systems (which has been acknowledged to be inconsistently reported and results are therefore indicative) and then redo the same analysis for HO systems.

Table 5 shows regression results for Equation 1 when the outcome is the transaction price per Watt of upfront TPO systems. The columns are arranged in the same way as in the previous regression Tables. Table C3 in Appendix C, shows regression results for the same sequence dropping observations in the vicinity of a subsidy level drop date. I recall the disclaimer, that all qualitative and quantitative conclusions related to the transaction prices of TPO systems are indicative, because transaction prices reported to the CSI may not necessarily represent what the consumer is actually paying to the TPO installer (see Section 3.5 for further details).

Column (6) shows that there is a large, positive and statistically significant association of the marginal subsidy level and transaction prices for governmental consumers. A one dollar increase of the subsidy level is associated with a 2.4 $ increase of the transaction price per Watt. Given average transaction prices per Watt range between 4 and 8 $ per Watt (see Table 2), this translates to 50 to 25 percent increase of the transaction price per Watt. This observation is in line with installers having different valuations for consumer types (i.e. with heterogeneity of λ in equation 2). The transaction prices of governmental consumers are ultimately paid by the tax-payer, which adds another layer of third party reimbursements and may reduce the extent to which installers care for the consumer's benefits λ leading to larger transaction prices.

Furthermore, residential consumers are associated with a larger transaction price per Watt. This association is however not statistically significant when dropping observations in the vicinity of a rebate level drop date (Table C3, Appendix C). A larger transaction price per Watt could again be attributed to less standardized installations in residential consumers, such as carport structures (see Gillingham et al., 2016, for a similar reasoning).

Next, Table 6 shows regression results for Equation 1 when the outcome is the transaction price per Watt of HO systems. The columns are arranged in the same way as in the previous regression Tables. Table C4 in Appendix C, shows regression results for the same sequence dropping observations in the vicinity of a subsidy level drop date.

The association of subsidy levels and the transaction price per Watt is positive and

Table 6: Transaction price per Watt of HO systems

	All obs. included					
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	0.234^{***}	0.298^{***}	0.233^{***}	0.297^{***}	0.384^{***}	0.402^{***}
	(0.035)	(0.047)	(0.035)	(0.047)	(0.090)	(0.102)
Field inspection (FI)						
FI = 1 × Subsidy level			0.247^{***}	0.312^{***}		
			(0.064)	(0.064)		
FI = 1			-0.095^{**}	-0.095^{*}		
			(0.037)	(0.037)		
Sector						
Government × Subsidy level					0.645^{**}	0.598^{*}
					(0.220)	(0.263)
Non-Profit × Subsidy level					0.649^{***}	0.715^{***}
					(0.107)	(0.119)
Residential × Subsidy level					0.245^{***}	0.295^{***}
					(0.036)	(0.047)
Government					0.440	0.506
					(0.260)	(0.314)
Non- Profit					-0.537^{***}	-0.590^{***}
					(0.114)	(0.127)
Residential					-0.137^{**}	-0.151^{**}
					(0.052)	(0.051)
N	69,113	69,113	69,113	69,113	69,113	69,113
1st-stage partial F-stat.	-	43965.8	-	87944.67; 33857.3	-	3102.2; 296.8; 1018.5; 1.2e+5

Notes: The outcome variable is the transaction price per Watt of HO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters, the experience of installers, the relative market power of installers and a measure for local industry concentration. The 1st stage partial F-statistics for the instrumental variables are 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.

statistically significant in columns (1) and (2). When interacting the subsidy level with a variable indicating whether the system is subject to a mandatory field inspection (*FI = 1*) in columns (3) and (4), we do not observe a significant difference of the marginal effect of the subsidy level with respect to field inspections (Wald test column 4, $H_0 =$ *Subsidy level = FI=1 x Subsidy level*, $p = 0.786$). At the same time, a mandatory field inspection is further associated with a statistically significant decrease of the transaction price per Watt of approximately 0.1 $ per Watt.

The marginal effects of the subsidy level on transaction prices per Watt by the consumer sector in columns (5) and (6) are all positive and statistically significant.

Pairwise comparisons of the coefficients show that the marginal effect for residential consumers is significantly lower than that of non-profit consumers (Wald test column 6, H_0 = *Non Profit x Subsidy level = Residential x Subsidy level*, $p < 0.001$). Finally, residential and non-profit systems are associated with a statistically significant decrease of the transaction price per Watt compared to commercial consumers.

These results suggest that a one dollar increase of upfront subsidies is associated with an increase of the transaction price per Watt of approximately $ 0.3 per Watt. Given average transaction prices per Watt range between 4 and 8 $ per Watt (see Table 2), this translates to a 7.5 to 3.7 percent increase of the transaction price per Watt. While mandatory field inspections do not reduce this association, they are associated with lower transaction prices per Watt, suggesting that they may trigger conservative pricing of installers as any surcharges are more likely to be detected.

The observation that the marginal effect of subsidy levels on transaction prices per Watt for non-profit consumers is the largest, is perhaps striking because non-profit organizations may be perceived as serving a good cause with little financial resources. There have, however, been some discussions on a decreased confidence in non-profit organizations as the sector is mostly unregulated and sometimes viewed as unethical as their good cause and "non-profit" status is doubted (O'Neill, 2009). This may in turn reduce the extent in how far installers care for the NPO's benefits λ and therefore lead to higher transaction prices.

In combination with the insights from Section 5.1, the results suggest that TPO installers do increase the design factor of residential consumers and at the same time only increase the transaction prices per Watt for governmental consumers. For HO systems, only the transaction price per Watt and not the design factor is increasing in the subsidy level. These insights are in line with increasing the short-term cash flow of installers, because directly after the installation TPO installers receive the total subsidies and HO installers receive the transaction price. In addition, the results can inform the subsidy pass-through of TPO installers as they increase the total amount of subsidies for residential consumers but do not adapt transaction prices accordingly which would ultimately lead to a larger pass-through.

6 Discussion and conclusion

In this paper, I studied 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 design factor as well as transaction prices per Watt of PV 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 such as an installer's market power, I find that TPO installers increase the design factor and thereby the total amount of subsidies received for residential systems. Such second-degree moral hazard on expense of the subsidy provider is however non-existent when the system is subject to a mandatory field inspection.

TPO installers do further not adapt transaction prices per Watt when residential consumers receive larger subsidy. In addition, the design factor of HO systems is unaffected by larger subsidy levels, but I find evidence suggesting that second-degree moral hazard increases the transaction prices per Watt paid by all consumer sectors. This is in line with a business strategy based on increasing short-term cash flows.

The results provide novel insights for 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 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 when installers can to some extent determine the total amount of subsidies received and ii) impose stricter verification measures on the work of installers.

Second, I document 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 second-degree moral hazard depending on increased verification and the bearer of the financial consequences (Balafoutas et al., 2013; Gottschalk et al., 2020). It is a promising route for future research to further uncover dimensions of heterogeneity in second-degree moral hazard as well as related solutions.

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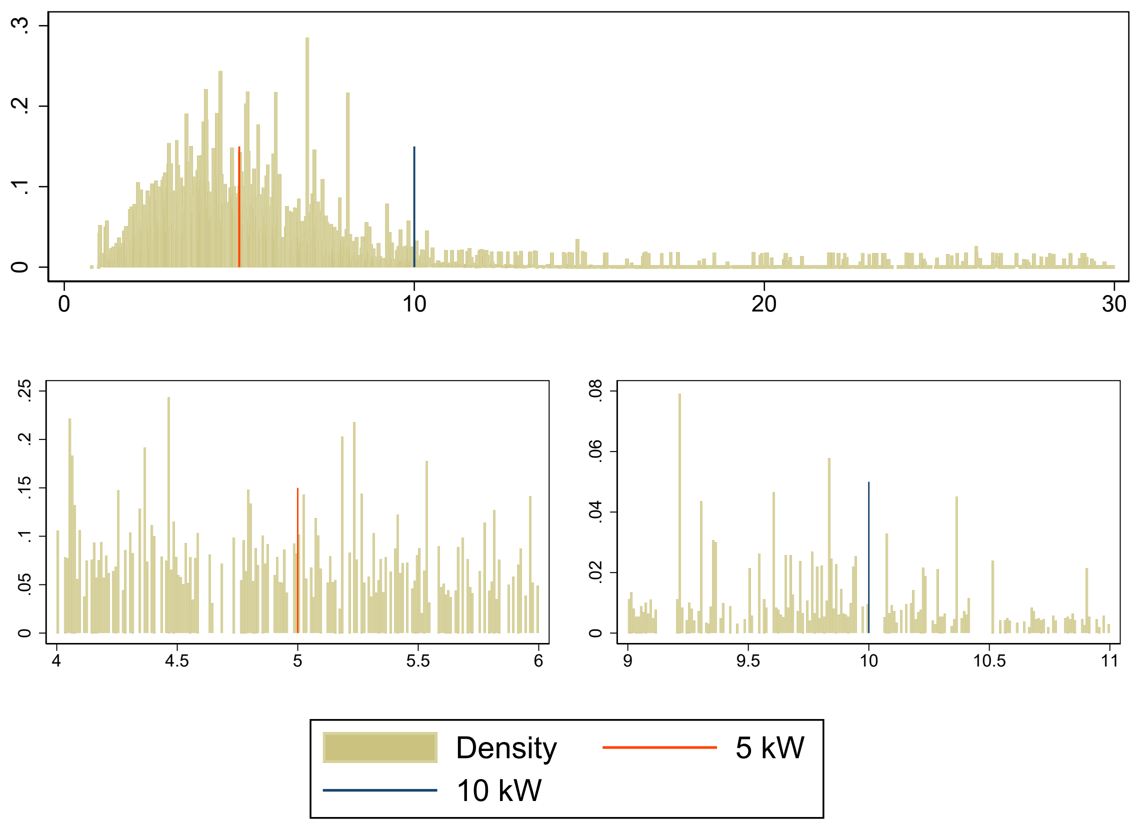
A Distribution of system size

Figure A1: Size distribution of upfront systems



Notes: Distribution of system size of upfront systems. The upper panel shows all upfront systems up to 30 kW. The lower left panel shows the distribution of the subset of system sized four to six kW. The lower right panel shows the distribution of the subset of system sized nine to eleven kW. The width of bins set to 0.01 kW.

Figure A1 shows the distribution of system size of upfront systems. As discussed in section 3.1, there is no evidence of bunching around a five or ten kW threshold, suggesting that strategic considerations do not play a role when choosing the system size.

Consumers installing a system sized between ten and 30 kW could choose to receive a different kind of subsidy which is paid conditional on actual electricity output rather then expected output. If for example, installers would want to maximize the upfront amount of subsidies received one would observe bunching of upfront systems with a size just below the threshold of 30 kW. We do not observe evidence for bunching around this threshold, suggesting that strategic self- selection into either subsidy type does not bias the results.

B First stage-regression results

Table B1: First stage regression results for Tables 3 and 4

	TPO (Table 3)			HO (Table 4)		
	(1)	(2)	(3)	(4)	(5)	(6)
Z_i	0.883^{***}	0.884^{***}	0.640^{***}	0.849^{***}	0.850^{***}	0.589^{***}
	(0.003)	(0.003)	(0.027)	(0.004)	(0.004)	(0.008)
Field inspection (FI)						
FI = 1 $\times Z_i$		0.989^{***}			0.965^{***}	
		(0.007)			(0.004)	
Sector						
Government $\times Z_i$			0.950^{***}			0.713^{***}
			(0.099)			(0.022)
Non-Profit $\times Z_i$			0.702^{***}			0.755^{***}
			(0.081)			(0.013)
Residential $\times Z_i$			0.973^{***}			0.987^{***}
			(0.006)			(0.002)
N	67,230	67,230	67,230	69,113	69,113	69,113

Notes: The outcome variable is the actually received subsidy level. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount 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 regression results for Tables 5 and 6

	TPO (Table 5)			HO (Table 6)		
	(1)	(2)	(3)	(4)	(5)	(6)
Z_i	0.883***	0.883***	0.641***	0.849***	0.850***	0.589***
	(0.003)	(0.003)	(0.027)	(0.004)	(0.004)	(0.008)
Field inspection (FI)						
FI = 1 × Z_i		0.989***			0.965***	
		(0.007)			(0.004)	
Sector						
Government × Z_i			0.950***			0.713***
			(0.099)			(0.022)
Non-Profit × Z_i			0.702***			0.755***
			(0.081)			(0.013)
Residential × Z_i			0.973***			0.987***
			(0.006)			(0.002)
N	67,230	67,230	67,230	69,113	69,113	69,113

Notes: The outcome variable is the actually received subsidy level. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters, the experience of installers, the relative market power of installers and a measure for local industry concentration. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.

C Additional Tables

Table C1: Design factor of TPO systems (Exclusion window)

	Exclusion window +- two weeks					
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Subsidy level	0.398^{*} (0.156)	0.552^{**} (0.172)	0.399^{*} (0.156)	0.552^{**} (0.172)	0.690 (0.781)	1.208 (0.709)
Field inspection (FI)						
FI = 1 × Subsidy level			−0.447 (0.459)	−0.221 (0.480)		
FI = 1			0.709 (0.449)	0.690 (0.447)		
Sector						
Government × Subsidy level					−3.668 (3.165)	−5.581 (4.416)
Non-Profit × Subsidy level					1.202 (1.191)	2.189 (1.905)
Residential × Subsidy level					0.400^{*} (0.156)	0.550^{**} (0.172)
Government					3.643 (3.062)	5.272 (4.044)
Non-Profit					1.207 (0.797)	1.319 (0.873)
Residential					-1.446^{***} (0.437)	-1.496^{***} (0.437)
N	61,456	61,456	61,456	61,456	61,456	61,456
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 the design factor of TPO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount 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 C2: Design factor of HO systems (Exclusion window)

	Exclusion window +- two weeks						
	OLS	2SLS	OLS	2SLS	OLS	2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)	
Subsidy level	−0.016	−0.046	−0.019	−0.049	0.013	−0.017	
	(0.111)	(0.126)	(0.111)	(0.127)	(0.225)	(0.267)	
Field inspection (FI)							
FI = 1 × Subsidy level			0.032	0.019			
			(0.170)	(0.183)			
FI = 1			−0.414*	−0.427**			
			(0.162)	(0.165)			
Sector							
Government × Subsidy level					−0.012	−0.388	
					(0.621)	(0.752)	
Non-Profit × Subsidy level					−0.442	−0.428	
					(0.319)	(0.355)	
Residential × Subsidy level					−0.018	−0.042	
					(0.111)	(0.126)	
Government					−0.805	−0.403	
					(0.816)	(0.981)	
Non-Profit					0.758	0.738	
					(0.389)	(0.415)	
Residential					−0.856***	−0.849***	
					(0.153)	(0.153)	
N	69,113	63,063	63,063	63,063	63,063	63,063	63,063
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 the design factor of HO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount 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 C3: Transaction price per Watt of TPO systems (Exclusion window)

	Exclusion windiw +- two weeks						
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	
Subsidy level	0.049 (0.028)	−0.008 (0.030)	0.049 (0.028)	−0.008 (0.030)	−0.083 (0.184)	−0.223 (0.219)	
Field inspection (FI)							
FI = 1 × Subsidy level			0.044 (0.151)	−0.028 (0.151)			
FI = 1			−0.088 (0.111)	−0.084 (0.111)			
Sector							
Government × Subsidy level					2.877* (1.133)	3.411*** (1.023)	
Non-Profit × Subsidy level					0.589* (0.300)	0.881 (0.460)	
Residential × Subsidy level					0.046 (0.029)	−0.008 (0.030)	
Government					−0.578 (0.802)	−1.057 (0.722)	
Non-Profit					0.353 (0.222)	0.417 (0.237)	
Residential					0.205 (0.128)	0.210 (0.129)	
N	69,113	61,456	61,456	61,456	61,456	61,456	61,456
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 the transaction price per Watt of TPO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters, the experience of installers, the relative market power of installers and a measure for local industry concentration. 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 C4: Transaction price per Watt of HO systems (Exclusion window)

	Exclusion window +- two weeks						
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	
Subsidy level	0.270^{***} (0.037)	0.298^{***} (0.047)	0.269^{***} (0.037)	0.297^{***} (0.047)	0.429^{***} (0.097)	0.416^{***} (0.105)	
Field inspection (FI)							
FI = 1 × Subsidy level			0.315^{***} (0.055)	0.333^{***} (0.062)			
FI = 1			-0.077^{*} (0.037)	-0.070 (0.038)			
Sector							
Government × Subsidy level					0.767^{**} (0.248)	0.671^{*} (0.302)	
Non-Profit × Subsidy level					0.677^{***} (0.109)	0.699^{***} (0.117)	
Residential × Subsidy level					0.282^{***} (0.038)	0.295^{***} (0.047)	
Government					0.357 (0.298)	0.463 (0.362)	
Non-Profit					-0.555^{***} (0.118)	-0.576^{***} (0.128)	
Residential					-0.136^{*} (0.056)	-0.141^{*} (0.055)	
N	69,113	63,063	63,063	63,063	63,063	63,063	63,063
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 the transaction price per Watt of HO systems. All specifications include fixed effects for the IOU, installer, month, sector as well as for make and models of modules and inverters. Further, all specifications include controls for the amount of modules and inverters, the experience of installers, the relative market power of installers and a measure for local industry concentration. Robust standard errors clustered at the zip code level are reported in parentheses. *, ** and *** denote statistical significance at 5%, 1% and 0.1% respectively.