On the Economics of Residential Solar PV Subsidies: Impact on Adoption and Savings

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Abstract

Ever since its advent, the adoption of renewable energy technology has received significant government support. However, there is limited empirical evidence on the effectiveness of subsidies that are used to promote renewable energy technology. Using a natural experimental setting where a solar PV subsidy is assigned randomly to applying households, we estimate the impact of subsidy provision on the adoption of solar PV, installed capacity, timing of the adoption and, ultimately, on electricity consumption. The results show that, within the group of households that applied for the subsidy, the provision of subsidy leads to a 14.4 percent increase in the probability of adopting solar PV, a 33.2 percent larger installation, and a 1 year faster adoption. However, examining the subsequent electricity consumption of the applicants, we report that the subsidy provision leads to a decrease in household electricity consumption of "just" 8.1 percent, as compared to the rejected applicant group, implying a cost of carbon of more than €2,202 per ton CO_2. The results of the paper show that the subsidy program mostly attracted the converted, although there might be spillover and other effects that may reduce the cost to somewhat lower levels.

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1 Introduction

In an effort to reduce the reliance on fossil fuels and the resulting carbon externality, stimulating renewable energy generation has become a vital aspect of public policy. Hence, many countries have set ambitious targets to increase the share of renewable energy in their primary energy mix. Given that the residential sector accounts for more than 25 percent of final energy consumption in the EU (Eurostat, 2020), it has been an obvious target for the renewable energy transition. In an effort to stimulate renewable energy generation among households, solar photovoltaic (PV) subsidies have been popular. According to Gielen et al. (2019), globally, solar PV received the largest share (48%) of renewable power generation support, with USD60.8 billion in 2017 alone. Especially at times when solar PV adoption was still slow, subsidies were introduced in order to provide a financial incentive to early adopters. These subsidies have been supplied in various forms, ranging from upfront and tax rebates, to production-based tariff subsidies.[1] Given that subsidies are costly to ratepayers, governments or both, the extent to which they achieve their desired environmental goals is a substantial question. Only when we understand how households respond to these financial incentives, future policies can be designed more effectively, in particular those boosting the uptake of (renewable) energy technologies in the early adopter stage (e.g. battery storage).

Although PV subsidy programs have been widely implemented across a large variety of countries, there is limited evidence on their effectiveness. There are only a handful of studies investigating the impact of subsidy programs on solar PV adoption. Bollinger and Gillingham (2012) study the California Solar Initiative (CSI), which provided $3.3 billion during a 10-year rebate program, aiming to achieve a surge in solar PV uptake. By exploiting differences in rebate levels in 33 ZIP codes alongside the border of two electricity providers in California, the authors find a lower adoption rate on the side of the border where the rebate scheme decreased. In another study, exploiting changes in actual rebate levels over time in California, Hughes and Podolefsky (2015) estimate that an increase in rebates from $5,600 to $6,070 would lead to a 10% increase in PV installations. They also predict that 47% of all households that were assigned the subsidy would have adopted solar PV, even without any rebate. Crago and Chernyakhovskiy (2017) study county-level data of 13 US states over the period 2005-2012, and exploit the variation in policies over time and across states. Their findings suggest that when the rebate level increases by 1 dollar

[1] In order to incentivize solar installations, countries generally use investment subsidies that refund part of the installation cost and/or feed-in tariffs/net metering mechanism in which producer is paid under a multi-year contract at a guaranteed rate.

per generated watt (a very handsome rebate), annual PV capacity increases by 47%. In a recent study, De Groote and Verboven (2019) investigate a generous Belgian subsidy program for solar PV adoption, and exploited rich variation in the future subsidy conditions at pre-announcement dates. Their results indicate that consumers discount the future benefits more when adopting solar PV. The sensitivity analysis finds some evidence for heterogeneity in discounting across consumers, indicating that future subsidy policies might have additional distributional effects, and require targeting of consumers with a low discount factor.

Although earlier studies provide useful information on impact of subsidy programs, there are some methodological concerns that need to be addressed to appropriately assess the impact of subsidies on solar PV adoption. Estimating the impact of subsidy programs requires knowing the amount of solar installation that would occur in the absence of the subsidy, which is not easy to observe. One approach might be comparing regions with different rebate levels. However, this might provide biased results as those regions presumably decide on subsidy policies based on the characteristics of the region and their residents. Besides, the regional rebate differences might be highly correlated with other energy policy instruments applied in those regions. In most of the available studies, these concerns are addressed through a quasi-experimental design. Using region-level data on solar adoption rates and over-time variation in regional rebate levels, these studies estimate the differential changes in adoption rates assuming parallel trends in solar adoption rates in the absence of treatment. However, in case the parallel trends assumption is violated due to differing characteristics of regions, these results might be biased. Besides, these studies assume that over-time change in rebate levels across different regions are uncorrelated with the changes in other characteristics of these regions that might also effect solar adoption rates. However, this assumption is hard to be satisfied in case policy makers decide on rebate levels based on the current adoption rates. An alternative approach for assessing the impact of subsidies might be analyzing individual level data on subsidy provision and adoption decision. However this approach also includes important endogeneity concerns, as PV subsidies tend to be more popular among households that are already planning to adopt solar PV, causing a self-selection bias.

Our paper complements the previous literature through providing a natural experimental setting in which the exogeneity assumption is satisfied by the help of random assignment of solar PV subsidies to applicants. Additionally, our paper complements the literature on household heterogeneity in subsidy effectiveness. Numerous papers examined the characteristics of solar PV applications as opposed to non-applicants.[2] We follow-up in this strand of studies by examining the heterogeneity of subsidy effects between (i.e. applicants versus non-applicants) and within groups. By using more granular data on the household level, we can see how individual households respond to subsidy provision, compared to the group of applicants that is rejected for the subsidy program after the lottery. In this way, we can identify which groups are most responsive to the subsidy, and which ones will adopt solar PV regardless of receiving the subsidy.

In this study, we explore the exogenous variation in subsidy provision to evaluate the effectiveness of a residential solar PV program in the Netherlands, a market which has been especially slow in the uptake of solar PV due to the local abundance of natural gas resources. However, in recent years, Dutch gas resources started running out while climate change concerns became more prominent. Hence, the Dutch government issued a production-based subsidy in the years 2008, 2009 and 2010, targeted at homeowners. At that time, solar PVs supplied just 0.01 percent of total energy consumption in the Netherlands (CBS, 2018). In order to get the first group of PV installers moving, the government issued a subsidy that was open to everyone. In all three years, this PV subsidy was oversubscribed, and a lottery decided on which applicants were offered the subsidy. Our data set covers all applying households, and we link their subsidy application details to the relevant household level characteristics. Additionally, we analyze 200,000 aerial images in order to identify whether, and if so when, applying households installed solar PV. Through this natural experimental setting, we can accurately estimate the average treatment effect on the treated by analyzing their solar PV installations and their subsequent energy consumption patterns. By studying the subgroup of applying households during the early stage of technology adoption, we learn how government subsidies affect households that are already primed to respond to renewable energy technology subsidies.

Our results show that the provision of subsidy leads to a 14.4 percent increase in the probability of solar PV adoption among the households that applied for the subsidy. The findings also indicate that, at the intensive margin, households that are accepted for the subsidy have a 33.2 percent larger installed capacity as compared to rejected households, and opt for installation about 8 months faster. Finally, examining the subsequent electricity consumption of the applicants, we report

[2]For instance, De Groote et al. (2016) find that presence of local policies and income have a positive effect on solar adoption in Flanders. Additionally, they say that the income effect is predominantly caused by the fact that wealthier households have a higher likelihood of adopting, because they are more likely to own the house, have a higher electricity usage, or own a house that is better suited for the PV installation. Jacksohn et al. (2019) explore the relative importance of different drivers of solar PV adoption through a german household panel. They find that, although household income and dwelling type influence the investment decision, economic factors are most important.

that the subsidy provision leads to a 8.1 percent decrease in households' electricity consumption as compared to the group of rejected applicants. Comparing the marginal energy savings with the cost of the subsidy program, we estimate that the subsidy has an implied a cost of carbon of more than €2,202 per ton. Clearly, there are more cost-efficient manners to reduce the carbon emissions from the residential real estate sector more generally, and when it comes to early adopters specifically, other methods may be more efficient. That said, our study does not take into account other effects, including possible spillover effects that the installation of solar PV by early adopters may have had on nearby residents, or the increase in salience of energy efficiency by applying householders, leading to spillover effects *within* homes, for example, the installation of more efficient light bulbs, insulation etc.

This paper proceeds as follows: section 2 gives a brief overview and background of the solar policy incentives in the Netherlands. Section 3 outlines our data sources and presents summary statistics, while section 4 discusses our empirical model and empirical findings. The most important results and policy implications are summarized in section 5.

2 The short history of (Dutch) solar policy incentives

Although the technology behind solar power dates back to the early nineteenth century – when the only 19-year-old Edmond Becquerel was the first to generate electricity by capturing sunlight – it has taken over another 150 years before governments recognized the potential and importance of upscaling solar energy.[3] Up until the early seventies solar power was mostly popular within the space program for powering satellites. In 1970 photochemist Elliot Berman teamed up with Exxon Mobile to build fsolar panels that would be economic for use on Earth. Their work gradually increased the efficiency of solar cells from 14 percent in 1970 to 36 percent in 1999, which fueled international investments in solar parks which currently outpace their fossil fuel alternatives.

The Netherlands has always been slow in its uptake of these solar power possibilities, partly due to the historic reliance on their local natural gas resources. By 2008, Dutch solar energy was virtually non-existing, and only 3.4 percent of the total Dutch energy use stemmed from renewable energy sources (the sum total of biogas, wind, biomass, solar and hydro). Around the same time, in 2008, The Renewable Energy Directive has set firm rules for the EU to achieve its

[3] In 1977 the US Government was the first to embrace the virtues of solar power, and stimulated the development of solar energy technology by launching the Solar Energy Research Institute.

20 percent renewables target by 2020.[4] This firm EU target, inspired the Dutch government to start stimulating renewable energy production actively. Hence, in 2008 the SDE (which is short for stimulating the production of sustainable energy) subsidy program was launched. These SDE subsidies made funds available for both firms and households and were designed after the price gap approach, compensating investors for the difference between the average market price per kWh and the cost per kWh. Back then, green energy was more expensive during production. Hence, the SDE subsidies offered financial compensation for these excess costs during the first 12 years of exploitation. These compensations were set and re-assessed every year, based on energy price realizations.

Back in 2008, a typical Dutch household consumed 3,400 kWh of electricity a year, a number which has remained almost constant over the years. The 2008 electricity price for Dutch household consumption (including taxes) equaled €0.23/kWh. In other words, the average household electricity bill in the Netherlands was around €780, a year. Installing 10 solar panels with a sum surface of 16 m^2 of 2008 quality would generate 1,550 kWh of solar electricity, resulting in a €355 reduction in the electricity bill. However, purchasing and installing these 10 panels in 2008 came at a cost of €9,350. This would imply a payback period of 26 years, which made solar panel installations financially unappealing for Dutch households.

This is where the SDE subsidies came in. They were made available in three rounds in the years 2008, 2009, and 2010, every year in two tranches; one for small scale (household) producers up to 15,000 kWh/year offering them €0.30/kWh in 2008, and one for large scale (15,000 – 1,000,000 kWh/year) producers offering €0.41/kWh in 2008. Obviously, these subsidies changed the household math of solar economics drastically. Assuming fixed electricity prices and subsidies over the twelve years that have past – and during which the first tranche of SDE subsidies paid out – consumers would earn €0.53 on every kWh of homemade solar electricity. This way the 1,550 kWh that would come from these 10 solar panels equaled a revenue of €820 a year, thereby cutting back the payback period to 11 years.

Hence, these SDE subsidies turned out very popular. For the first time, Dutch private households could apply for solar subsidies, they did so and in large numbers. In 2008, 2009 and 2010 around 15,000 applications were made in total after opening, which was April 1st. Applications could be handed in both on paper and digitally. Since the first took more time

[4] See https://ec.europa.eu/energy/topics/renewable-energy/renewable-energy-directive_nl for more details on The EU Renewable Energy Directive. The 20 percent 2020 target is spread unevenly across Europe, accounting for natural endowment effects. For the Netherlands the 2020 target for renewable energy production was set at 14 percent.

for processing, the government authority responsible for issuing these subsidies first collected all applications and then organized a lottery to select granted applications. After being accepted to the subsidy program, applicants had 4 years to complete the solar PV installation in order to be able to claim the compensation. For the 12 years following solar PV installation, the household received a compensation for every kWh of generated electricity. If not accepted, households could apply to the subsidy again in the next year.

3 Data

In order to investigate the impact of solar PV subsidies on household's solar adoption decision and their subsequent energy consumption, we benefit from a data set obtained from the Netherlands Enterprise Agency (RVO), which provides information on the applicants of solar PV subsidy programs implemented in years 2008, 2009, and 2010. The sample includes 14,891 households. From this source, we know the address of the households that applied to the subsidy program and whether they are accepted or rejected for the subsidy based on a lottery. We complement this data with information gathered through aerial images. These images were shot on a yearly basis from 2007 to 2016 by means of an aircraft. We match these pictures to the addresses of subsidy applicants and manually analyze the presence of a solar panel installation on the rooftop. Contrary to detecting satellite images for solar panel presence through an algorithmic approach, we create a data set with a close to 100 percent accuracy on solar panel presence. The limitation here is that this approach does not easily allow to create a data set of solar panel presence for the complete population. However, this is no major concern for our analysis since we are focusing on the subgroup of applicants that applied to the solar PV subsidy. Through the randomization process provided by the subsidy lottery, we have a comparable control group and we do not need data on the total population for our analysis. The aerial shots provide us with information on whether, and if so when, households adopted solar panels from 2007, i.e. 1 year before the subsidy application, until 2016. For the realized installations, we can also identify the size and number of installed panels. We merge this data with detailed household level information about the occupants and their electricity consumption provided by the Central Bureau of Statistics in the Netherlands (CBS). The CBS data includes information on annual electricity consumption, household composition, income, wealth, education level, dwelling size, type and construction year. In addition to the sample of subsidy applicants, we also include a random 1% sub-sample of the non-applicants in all three subsidy years.

We removed outliers at the upper and lower 1% level for electricity consumption, surface, income, and wealth. Additionally, we excluded observations where annual electricity consumption is zero. We also excluded households that applied to the program multiple times in the three years [5], and households that moved during the sample period. In this way, we end up with a sample of 4,439 applicants and 161,929 non-applicants.

Table 1 - columns 1 and 2 provide the descriptive statistics for the applicants and the non-applicants in the years before the subsidy application. The statistics indicate that there are significant differences in observable characteristics between these two groups. Households who apply to the subsidy program on average consume more electricity, are younger, have a larger household size, more children, higher income and wealth, and a higher education level. They are also more likely to live in semi-detached or detached dwellings, and in relatively new (1990+) dwellings. Table A.1 - column 1 in the appendix provides the estimation results for a logit regression model that assess the determinants of subsidy application. Complementary to Table 1, these results indicate that household and dwelling characteristics have a significant impact on the decision to apply for the solar PV subsidy. From this observation, we can clearly see that there is a sorting effect. This finding is in line with Allcott et al. (2015) showing that in the absence of targeted policy, there will be a certain group applying to subsidy programs for energy efficient durable goods. In their case, this group consists of wealthy homeowners that face less credit constraints, and that are more likely to be interested in solar panel adoption.

— Insert Table 1 —

Once households applied to the subsidy program, their acceptance to the program was decided by a random draw. In line with expectations, Table 1 - column 5 proves that there are no significant differences in observable characteristics across accepted and rejected households. Additionally, Table A.1 - column 2 in the Appendix provides the estimation results for a logit regression model, where subsidy acceptance is the dependent variable. The results support that subsidy acceptance is indeed randomly assigned.

[5]There were eight households that applied twice, and also eight that applied to all three subsidy years. Since this number of households is relatively small, we do not perform a separate analysis on this group and drop these observations.

4 Methodology and Results

In order to estimate the impact of subsidy programs on solar panel adoption decision, we need to know what would happen in the absence of the subsidy. In this study, we use the exogenous variation in subsidy provision to identify the impact of subsidy provision. As subsidies are assigned based on a random draw, we are able to compare accepted and rejected subsidy applicants. By the help of the random assignment rule, we can estimate the Average Treatment effect on the Treated (ATT). In the case of a policy intervention where a specific group sorts into the program, an evaluation problem can occur by observing no counterfactual. Contrary to estimating the Average Treatment Effect (ATE), the ATT removes the selection effect by providing a counterfactual group that is similar in both observable and un-observable characteristics, but did not receive treatment. ATT is therefore found to be useful in estimating the effectiveness of policy instruments on the subsidy receivers. The method applies to a setting where there is an initial group of applicants identified, after which a random process determines who will be accepted to receive program benefits.Following Heckman et al. (1997), the ATT parameter is defined as:

$$E(Y_{i1}|D=1,R=1) - E(Y_{i0}|D=1,R=0) = E(\Delta Y_i|D=1) \tag{1}$$

Where D = 1 denotes application to the subsidy program, and R = 1 the acceptance to that program determined by a random process. The treatment effect of the subsidy program is the outcome of the rejected applicants subtracted from the outcome of the accepted applicants (ΔY_i). This net effect is the total program effect, i.e. the outcome if all applicants would have been accepted to the subsidy program.

In this paper, we investigate the impact of a subsidy program on two types of outcomes. First, we consider the effect of acceptance to the subsidy program on the decision to adopt solar PV, investment size and its timing. Thereafter, we examine how the subsidy program affects end use in electricity consumption. In order to examine the impact of subsidy provision on these outcome variables, we propose the following empirical model:

$$Y_i = \beta_0 + \beta_1 Accepted_i + \beta_2 X_i + T_i + \epsilon_i \tag{2}$$

where Y_i denotes the outcome variable for household i. For the adoption decision the outcome variable takes 1 if household installs solar panel during the period of analysis and zero otherwise.

Moreover, we also consider how size of the panel installation is affected by the acceptance to the subsidy program. As another and final outcome variable, we also consider the number of years between applying for the subsidy program and installing solar panels. For these outcome variables, we perform a cross sectional analysis on all households that adopted solar PV. $Accepted_i$ denotes whether household i is accepted to the subsidy program. X_i is a vector of home and household characteristics. T_i is an application year fixed effect, for the three different application years of the subsidy program and ϵ_i is the error term, assumed to be independent from subsidy provision and normally distributed.

4.1 Solar PV Adoption

Given that subsidy is assigned randomly, first we check how these two group of households respond to subsidy provision based on descriptive statistics. For all subsidy applicants, we know whether they installed solar panel between 2008 and 2016. If they install the solar panel, we can also identify the size and timing of the adoption from areal imagery. In Table 2, the descriptive statistics of the solar PV adoptions are displayed for every subsidy year, split up for accepted and rejected applicants. Firstly, we can see that in the first year of the program most of the applicants were accepted into the program. In the second year, the amount of accepted and rejected households was more even. Then, in the last year, the largest part of the applicants was not assigned any subsidy. In the subsidy programs of 2009 and 2010, it is also visible that subsidy provision led to a larger total size of the panels. We see that accepted applicants are significantly more likely to adopt solar panels in all subsidy years. However, in the group of rejected applicants, still more than half of all households installed solar panels within the observation period. Multiple mechanisms could be at play here. Firstly, it could be the case that the application process itself is already what motivates households to invest in a PV installation. They overcame the barrier of filling in the forms and investigating suppliers, and their investment decision is only partly affected by whether they receive the subsidy or not. [6] Moreover, the subsidy application process could simply identify those that are already planning to adopt solar PV. With our observed data it is hard to draw conclusive insights on which, combination of, factor(s) is at play here. One thing we can do is consider the timing of adoption after the subsidy application year. Here we see that the rejected

[6]For instance, Fowlie et al. (2015) investigate the Weatherization Assistance Program in Michigan, a program aimed at increasing investment in energy efficiency measures for the home. They find that, even when investment costs were fully covered and significant effort was put in persuading households, participation in the program only increased slightly. Their findings indicate that non-monetary costs, such as paperwork, are a significant barrier towards investment.

subsidy applicants delay their adoption compared to accepted applications. This would suggest that both of the above-mentioned effects are at least not the complete story, as we would then see an immediate adoption in the rejected applicant group as well.

— Insert Table 2 —

Next, we estimate a logit model based on the empirical model in equation (2), in which the dependent variable is a binary variable that takes one if the household install solar panel within the period of analysis, and zero otherwise. In Table 3, we report the average marginal effects for the logit model.[7] Columns 1 and 2 present the sub-sample estimation results for which we have information on household and home characteristics. Comparing these result, we conclude that adding the control variables to the model does not lead to a significant difference in the estimated effect of subsidy provision on the solar adoption decision, which also supports the exogeneity of subsidy assignment. Therefore, in column 3, we provided the full-sample estimation results without controlling for the household and home characteristics. We observe that acceptance to the subsidy program has a significant and positive impact on solar adoption. Being accepted to the subsidy program leads on average to a 14.4% increase in the chance to adopt solar PV.[8] Our result is in line with previous literature that finds a significant role for financial incentives in the adoption of solar panels (Bollinger and Gillingham, 2012; Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy, 2017; Jacksohn et al., 2019). With the subsidy offering on average €0.52 per kWh, while electricity in the period costed on average €0.23/kWh, the payback period was cut by 11 years. Given this benefit, the effect size that we find seems to be limited. However, this result is reasonable given our estimation method. The previous literature compares adopters with non-adopters in a quasi-experimental setting. In this study we do not look at the average treatment effect of the total population, but the subsidy effect on a selected group applicants. We would now expect a smaller effect size compared to previous literature. That is because the applicant group is already more likely to adopt solar panels compared to the total population, and the effect in previous studies could be partially driven by a selection effect. For instance, Hughes and Podolefsky (2015) estimate that 47% of subsidy receivers in their study would have adopted solar PV regardless of the subsidy. Therefore, the 14.4% that we find can be a reasonable finding of the additional effect of subsidy on

[7]Table A.1 in the appendix provides the raw results for the logit estimation.

[8]Moreover, there is a significant effect on the solar adoption decision for the number of children and elderly, the type of dwelling, and the building year of the dwelling. The number of children and number of elderly in a household decrease the chance of adopting solar PV by 4.64% and 2.54% respectively. We conclude that acceptance to the subsidy program is the most significant and largest driver of solar adoption among the applicants.

solar adoption among the selected group of applicants, i.e. the households that were motivated to respond to the subsidy application.

— Insert Table 3 —

We also check how subsidy provision affects the total PV investment size of households. Focusing only on the binary adoption decision might provide misleading results as the subsidy might also affect the size of their investment. Table 3 - Columns 4 and 5, which report the results for the matched sample, show again that including the control variables to the model does not change the effect size. The full sample in column 6 shows an effect of 33.2%. Thus, by looking at the panel size of installers in the treatment and control group, we see that the subsidy has a positive and significant influence in the installed PV capacity.

Next, we check whether there is a difference in the timing of PV adoption between accepted and rejected applicants. We track the PV installation decisions of subsidy applying households until 7 years after their subsidy application. Figure 1 shows that more than 30% of accepted applicants install solar PV in the year of application, or the first year after that. On the contrary, solar PV adoption among rejected applicants is more spread out over the years. The percentage of rejected applicants that install panels in the year of application or the subsequent year is around half of the percentage in the accepted group. As highlighted by De Groote and Verboven (2019), in the early stage of a new technology, timing of adoption is an important consideration in the investment decision. Because of rapidly decreasing costs and increasing quality, it can be worthwhile to wait, even if an investment would already be profiTable at that moment. The delayed investment in the rejected applicants group is in line with this reasoning. Besides, these household are not motivated by installing solar PV before a certain date, after which their subsidy benefits could not be claimed anymore. When accepted to the subsidy program, the households are forced to install solar PV within 4 years. This is also the reason why there is a small jump in the percentage of installers visible in year 5 for accepted applicants. This group was reminded of the expiration of their rights, and installed the PV panels just before the deadline. Thus, subsidy provision not only significantly increases solar adoption, but also moves the adoption decision forward.

— Insert figure 1 —

Table 4 provides the OLS estimation results of equation 2, for which the outcome variable is the number of years passed between subsidy application and adoption. Among adopters, the acceptance to the subsidy program leads to a faster adoption of a little more than 1 year, 1.07.

— Insert Table 4 —

4.2 Heterogeneity Analysis

Table 5 reports a heterogeneity analysis of the effect of subsidy acceptance on solar PV adoption. We interact the dummy that indicates acceptance to the subsidy program, with a dummy that equals one if a household falls in the upper 50% of the distribution of a certain variable. In this analysis we see if the relationship is heterogeneous across different levels of age and wealth of the household. In this way, we assess here how the responsiveness to subsidy acceptance is influenced by these observable household characteristics. Once accepted to the subsidy program, a household can still decide on whether or not to invest in solar PV panels. For both age and wealth, we can see that there is no significant interaction effect observable in this sample. Both of the interaction terms hint at a negative relation between the a higher age and wealth, compared to the lower 50%. However, the standard errors are too large too reject the null hypothesis of no effect. The decision to adopt solar panels could be less affected by the provision of subsidy for wealthier and older households. The relation with wealth could be explained by the fact that the subsidy reduces the payback period substantially and this may be a more important factor for households with lower wealth. Regarding age, it would be likely that the age of the household is also related to their level of wealth and that the effect could be explained by the same reasoning. To draw more conclusive insights on these mechanisms, a larger sample size would be of use.

— Insert Table 5 —

4.3 Electricity Consumption

The underlying aim of subsidizing renewable energy technologies is to decrease grid energy consumption, which is mostly based on fossil fuels. Our earlier results indicate that subsidy provision increases the adoption of solar panels. However, this does not imply that it has proportional impact on grid-based final energy use. The access to solar power at near zero marginal costs may well induce rebound effects which shift households' demand curve and distort the net effects of solar PV investments. The rebound effect, or "*takeback*", is described as the loss in expected gains from an efficiency-increasing technological change that is caused by a behavioral change (Berkhout et al., 2000). It is a widely-researched concept for various efficiency-increasing technologies.[9] On the other hand, there are only a few papers that estimate a solar rebound effect for households. Analyzing billing data for the period 2007–2014 on a sample of 4,819 households in Sydney, Deng and Newton (2017) document a rebound effect of around 21 percent. Using household level high frequency electricity consumption and production data from 277 solar homes in Phoenix Arizona, Qiu et al. (2019) found that when solar electricity generation increases by 1 kWh, solar PV homes increase their total electricity consumption by 0.18 kWh.

Therefore, in this study we also examine how subsidy provision affects the final grid-based electricity consumption. Figure 2 compares yearly electricity consumption of accepted and rejected applicants, and non-applicants over time for the three subsidy waves. We measure net electricity consumption, meaning that all solar generated electricity is deducted from the household's electricity consumption. There is a clear pre-trend visible for the applicants, as electricity consumption in the accepted and rejected group is similar before the assignment of subsidy benefits. Moreover, the electricity consumption of applicants far exceeded those of non-applicants during the pre-subsidy period. For all three groups, we see that electricity consumption goes down over time. The decline is steepest for the accepted applicants, and smallest for the non-applicants. For the rejected and accepted applicants, the gap in electricity use first widens, but then becomes more narrow over time. This can be explained by the lagged solar panel installation, as displayed in figure 1 above.

— Insert figure 2 —

Next, we estimate whether their is a significant net effect in grid-based electricity consumption between the accepted and rejected applicants, in the short and long run. The empirical model is as follows:

$$ln(Electricity_{it}) = \beta_0 + \beta_1(Accepted_i * Post_t) + \beta_2 Accepted_i + \beta_3 Post_t + T_t + \epsilon_{it} \tag{3}$$

where the dependent variable is the log net electricity use of household i in time period t. $Accepted_i$ is a dummy variable indicating whether household i is accepted to the subsidy program. $Post_t$ is a dummy variable that equals 1 if period t is after the subsidy application year. The subsidy application year is excluded from the analysis. ϵ_{it} is the error term, which is assumed to be random and normally distributed.

[9]See Sorrell et al. (2009); Aydin et al. (2017).

The results of the model of equation 3 can be found in Table 6. When we consider the sub-sample that we were able to match to the household characteristics, we only observe a long run effect. After 1 year, there is no significant difference between the treatment and control group in electricity consumption. This could have to do with the limited sample size. After 5 years, there is a 2.94% decrease in electricity consumption in the subsidy receiving group of adopters, compared to the solar PV adopters that did not receive subsidy. Without controlling for household characteristics, the sample becomes larger and we find a significant treatment effect after 1 year and after 5 years. We also see that including the household characteristics leads to similar a similar effect size, which is in line with expectation given our exogeneous treatment assignment which would eliminate the effect of omitted variables. If we regard the full sample of applicants, we see that acceptance to the subsidy program leads to a 5.92% decrease in grid electricity use in the post treatment period during the first year. This effect is still significant after 5 years and increases to 8.10%.

To judge the size of this electricity reduction relative to the program costs, we perform a back of the envelope calculation. With an average yearly electricity use of 4,026 kWh in the applicant group, yearly realized electricity savings from the subsidy program are 326 kWh. Considering a lifespan of 25 years for a solar panel installation, the total additional electricity savings are 8,153 kWh per household that received subsidy. Over 25 years, this means that the overall electricity savings are around two years in electricity use. We can regard this as a relatively small yield. Given our empirical approach which isolated the additional effect of subsidy provision on the households that are already inclined to respond to renewable energy technology subsidies, the result is not surprising. The effect that we find is limited, because the subsidy is partly provided to households that would install the panels regardless of whether they receive subsidy.

In order to assess the cost-effectiveness of this subsidy program, we relate the electricity savings to the program costs. 5216 households received a total of €52 million. The total savings in kWh are 42.5 million. Per kWh, the program thus spent €1.22. In terms of tons of CO_2 reduced, this would transfer to 23,610 ton. Per ton of CO_2, €2,202 was spent. In the EU ETS market, the same unit of reduction costed around €26 in 2008. In terms of electricity savings achieved through the program, we can thus conclude that CO_2 reduction came at a substantial cost. Comparing to previous literature evaluation solar panel subsidies in the residential market, the cost that we find is also substantially higher. For instance, the cost of mitigating CO_2 per ton was between \$130 and \$196 in Hughes and Podolefsky (2015), \$184 in Crago and Chernyakhovskiy (2017), and \$364 in Gillingham and Tsvetanov (2019). This substantial difference can have two explanations. Firstly, we consider a different program structure in another country. Secondly, with our methodological approach we are able to estimate an ATT instead of an ATE, which could lead to a smaller effect size and thus a higher program cost per unit of savings.

— Insert Table 6 —

4.4 Heterogeneity Analysis

In Table 7 we present a subsample analysis for the relation between subsidy acceptance and electricity consumption. We identify different groups based on observable characteristics and see how these characteristics influence the extent to which households change their electricity consumption after being accepted to the subsidy program. As in Table 5, we focus on age and wealth. Age of the household head does not alter the relation between subsidy acceptance and electricity consumption. Households with a higher wealth level in the treatment group reduce their electricity consumption more, compared to lower income and wealth households. One reason explaining this effect could be that the wealthier household place more solar panels on their roofs. However, when consider the standard errors of these coefficients, we can not say that there is a significant difference across different household wealth levels. Similar to the heterogeneity analysis concerning solar adoption in Table 5, we can say that we would probably need a larger sample to investigate heterogeneity more thoroughly.

— Insert Table 7 —

5 Conclusion

Solar PV installations are an important means to increase renewable energy production, given the ease of distributed installation, on rooftops of homes and commercial real estate buildings. To stimulate the adoption of solar PV by homeowners, many governments have used a variety subsidy programs targeting residential households. In the early years of the technology, such subsidies were especially popular, and were aimed at promoting a new technology and reducing the negative external effects of fossil fuel use. Although there is widespread use of this policy instrument across countries, evidence on the effectiveness of such programs is limited. The few existing studies that investigate the impact of solar PV subsidies on subsequent adoption typically make use of a quasi-experimental approach to assess the effectiveness of subsidy provision on the reduction of CO_2 emissions. However, the presence of random policy assignment and parallel trends is easily violated here, and there exists a real concern for selection bias. In our study, we address this issue through analyzing a natural experimental setting, where we can exploit exogenous variation in the subsidy assignment.

We analyze a solar PV subsidy program in the Netherlands from 2008 to 2010. The program offered a production-based compensation and targeted residential households. Due to an over-subscription to the subsidy program, a lottery decided which households were accepted to receive benefits. Through analyzing 200,000 aerial shots, We observe the actual solar adoption decision of all applicants, and we combine this unique data set with detailed micro data on household characteristics and energy use. We compare this data across the groups of applicants that were accepted or rejected for the program. With a clean control group, we can thus measure the effect of providing subsidy on subsidy applicants. This informs us about the effect of such policy incentives on households that are inclined to respond to the subsidy application.

Using a logit estimation, we show that acceptance to the subsidy program leads to a 14.4% increase in the likelihood to install solar panels. Moreover, we find that providing the subsidy also affects other aspects of the adoption decision. In a cross-sectional analysis, we find that accepted applicants that adopt solar panels do this 1.07 year faster, and install solar PV capacity that is 33.2% larger. Subsequently, we assess the effect of subsidy provision on electricity consumption. The results of the difference-in-difference analysis show that accepted applicants have a 8.1% lower electricity consumption, annually, as compared to the rejected applicants, in the period 5 years after the installation of solar PV.

The results highlight that, without targeting, a subsidy program tends to attract a select group of applicants. This group is wealthier, higher educated, younger, and uses more electricity. We show that, within this group, giving a subsidy leads to a higher adoption rate, whereas the solar PV is also installed earlier and in larger quantity. Moreover, we observe that overall electricity use is lower. Although we find a significant effect, it is questionable whether this was a cost-efficient allocation of taxpayer money. In order to assess the cost-effectiveness of this public spending towards achieving the mitigation of CO_2 emissions, we compare the costs of CO_2 emissions in this program with the market price of CO_2. A back of the envelope calculation reveals that the costs to reduce CO_2 emissions by one ton with this subsidy program were €2,202. In 2008, the market price for one ton of CO_2 in the EU ETS system was €26. This finding implies that mitigating CO_2 emissions through the subsidy program came at a substantial cost.

However, we solely evaluate the direct effect of the subsidy on electricity saving in this study.

Potentially, solar adoption by the subsidy receiving households had spillover effects that we do not measure at the moment, and that would justify the provision of subsidy. Future research, for example, could investigate whether the PV installations of the subsidy receivers triggered adoption by other households, an effect which has been found in e.g. Bollinger and Gillingham (2012). Additionally, it could be that the solar subsidy leads to spillovers *within* households, i.e. their investment in solar panels leads them to invest in other renewable energy or energy efficient technologies in their home. Furthermore, the promotion of technological development, which would lead to lower production costs, would be another factor to take into account (Van Benthem et al., 2008).

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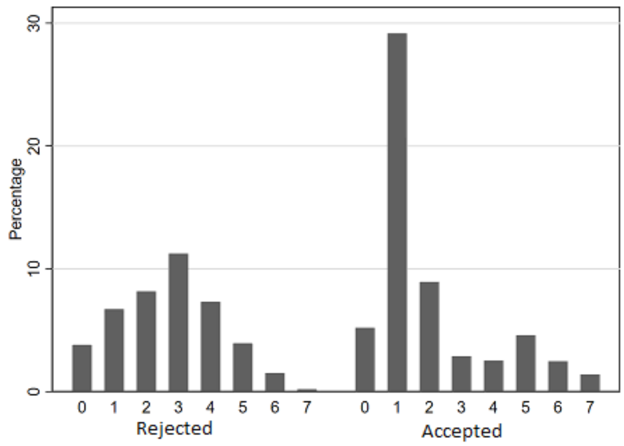
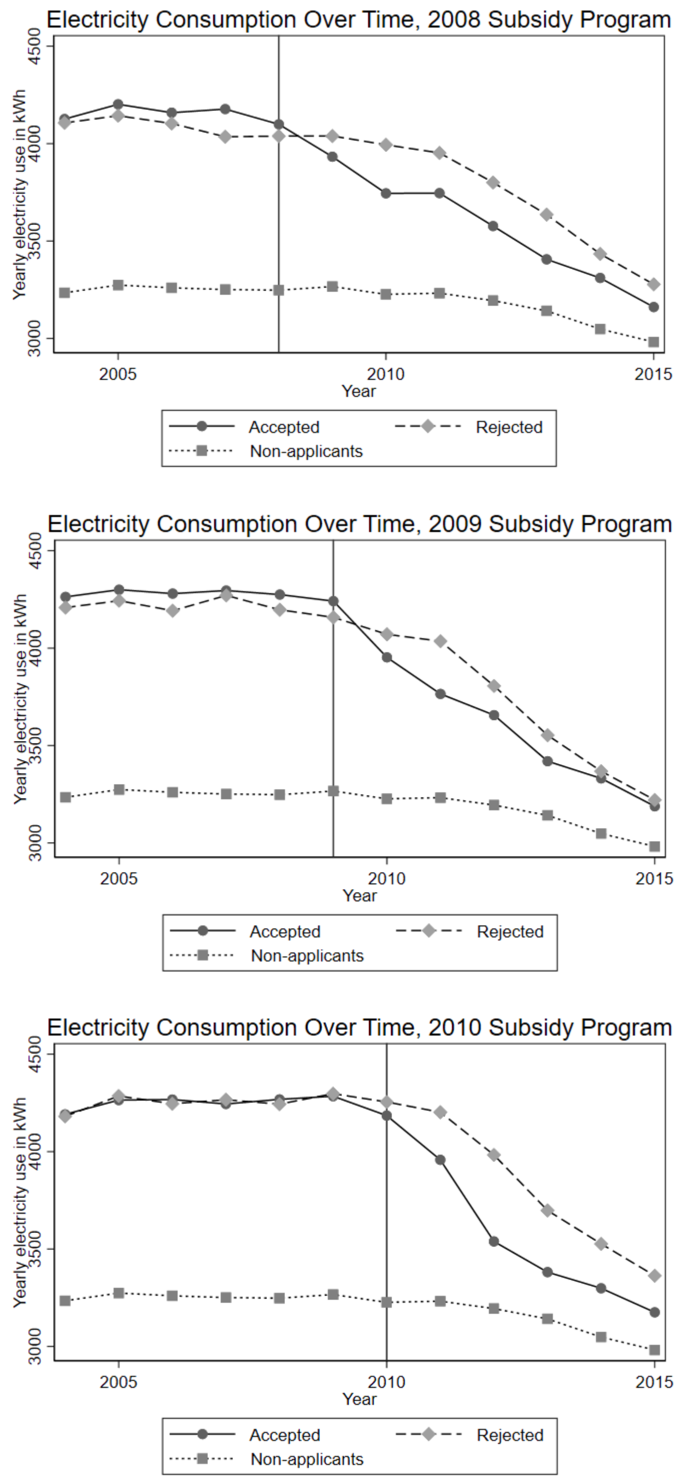
Figure 1: Time between subsidy application and solar adoption



Notes: The figure presents the timing (in years) of PV adoption for accepted and rejected applicants separately.

Figure 2: Electricity Consumption Over Time



Notes: This figure presents yearly electricity consumption of accepted and rejected applicants, and non-applicants over time for the three subsidy waves. We measure net electricity consumption, meaning that all generated electricity is deducted from the household's electricity consumption.

Table 1: Descriptive Statistics

	(1) Applicants	(2) Non-applicants	(3) T-test	(4) Accepted applicants	(5) Rejected applicants	(6) T-test
Annual Electricity consumption (kWh)	4,026	3,047	-979***	4,012	4,042	30
	(1,623)	(1,520)	(23)	(1,610)	(1,637)	(48)
Number of household members	2.718	2.030	-0.688***	2.717	2.720	0.003
	(1.252)	(1.111)	(0.0170)	(1.254)	(1.250)	(0.037)
Age of household head	51.884	56.655	4.771***	51.776	51.998	0.222
	(11.68)	(15.68)	(0.237)	(11.67)	(11.70)	(0.351)
Number of children	0.704	0.334	-0.370***	0.698	0.710	0.012
	(1.064)	(0.775)	(0.011)	(1.065)	(1.064)	(0.032)
Number of elderly (>65)	0.515	0.651	0.135***	0.504	0.527	0.023
	(0.987)	(0.904)	(0.013)	(0.988)	(0.986)	(0.029)
Number of females	1.168	0.953	-0.215***	1.169	1.167	-0.002
	(0.888)	(0.730)	(0.011)	(0.877)	(0.899)	(0.026)
Annual household income (€1000)	45.997	30.711	-15.286***	45.824	46.180	0.356
	(17.48)	(15.16)	(0.232)	(17.24)	(17.74)	(0.525)
Household wealth (€1000)	289.1	144.2	-144.9***	286.3	292.0	5.705
	(222.5)	(183.0)	(2.802)	(217.3)	(227.9)	(6.682)
Education level:						
Primary school	0.007	0.040	0.033***	0.005	0.008	0.003
	(0.081)	(0.196)	(0.002)	(0.072)	(0.091)	(0.002)
Secondary school	0.018	0.046	0.027***	0.018	0.019	0.001
	(0.135)	(0.209)	(0.003)	(0.133)	(0.137)	(0.004)
Vocational school	0.108	0.144	0.036***	0.105	0.111	0.006
	(0.310)	(0.351)	(0.005)	(0.307)	(0.314)	(0.009)
Higher vocational school	0.187	0.082	-0.105***	0.188	0.186	-0.002
	(0.390)	(0.275)	(0.004)	(0.391)	(0.389)	(0.011)
Bachelor degree	0.012	0.005	-0.007***	0.010	0.013	0.003
	(0.108)	(0.067)	(0.001)	(0.0999)	(0.115)	(0.003)
Master/PhD degree	0.122	0.039	-0.083***	0.134	0.109	-0.025
	(0.320)	(0.188)	(0.002)	(0.331)	(0.308)	(0.009)
Dwelling type:						
Apartment	0.034	0.271	0.237***	0.035	0.034	-0.001
	(0.182)	(0.445)	(0.006)	(0.183)	(0.181)	(0.005)
Corner house	0.157	0.159	0.002	0.160	0.154	-0.006
	(0.364)	(0.366)	(0.005)	(0.366)	(0.361)	(0.010)
Semi-detached house	0.159	0.103	-0.056***	0.160	0.158	-0.002
	(0.366)	(0.304)	(0.004)	(0.367)	(0.364)	(0.011)
Between house	0.288	0.358	0.070***	0.298	0.278	-0.020
	(0.453)	(0.479)	(0.007)	(0.457)	(0.448)	(0.013)
Detached house	0.362	0.109	-0.254***	0.348	0.377	0.029*
	(0.481)	(0.311)	(0.004)	(0.476)	(0.485)	(0.014)
Building construction year:						
1900-1929	0.103	0.085	-0.018***	0.101	0.106	0.004
	(0.305)	(0.279)	(0.004)	(0.302)	(0.307)	(0.009)
1930-1944	0.074	0.065	-0.008*	0.077	0.070	-0.007
	(0.261)	(0.247)	(0.003)	(0.267)	(0.256)	(0.007)
1945-1959	0.062	0.113	0.051***	0.064	0.059	-0.005
	(0.241)	(0.317)	(0.004)	(0.246)	(0.236)	(0.007)
1960-1969	0.094	0.163	0.069***	0.094	0.094	-0.000
	(0.291)	(0.369)	(0.005)	(0.292)	(0.291)	(0.008)
1970-1979	0.174	0.197	0.023***	0.175	0.172	-0.003
	(0.379)	(0.398)	(0.006)	(0.380)	(0.378)	(0.011)
1980-1989	0.142	0.178	0.036***	0.138	0.145	0.007
	(0.349)	(0.383)	(0.005)	(0.345)	(0.353)	(0.010)
1990-1999	0.235	0.146	-0.089***	0.229	0.241	0.012
	(0.424)	(0.353)	(0.005)	(0.421)	(0.428)	(0.012)
>2000	0.117	0.052	-0.064***	0.120	0.113	-0.008
	(0.321)	(0.222)	(0.003)	(0.325)	(0.316)	(0.009)
Number of observations	4,439	161,929	166,368	2,281	2,158	4,439

Notes: Table presents the descriptive statistics for all solar PV subsidy applicants, non-applicants, accepted and rejected applicants separately. Column 1 provides information on all subsidy applicants in the years 2008, 2009, and 2010. The statistics are calculated based on the year before subsidy application. Column 2 includes a random 1% of the sample of all Dutch households that did not apply to the subsidy program. Columns 4 and 5 split up the group of applicants into the ones that were accepted and rejected for the subsidy program as a result of the lottery. Standard deviations are given in parentheses. Columns 3 and 6 indicate the statistical significance of the differences in variables between two groups. Standard deviations are reported in parenthesis. * P<0.05. ** P<0.01. *** P<0.001

Table 2: Descriptive Statistics Subsidy Program

	Subsidy year: 2008			Subsidy year: 2009			Subsidy year: 2010		
	(1) Accepted	(2) Rejected	(3) T-test	(4) Accepted	(5) Rejected	(6) T-test	(7) Accepted	(8) Rejected	(9) T-test
Solar adoption	0.676	0.524	-0.151***	0.667	0.560	-0.117***	0.691	0.520	-0.171***
	(0.468)	(0.500)	(0.021)	(0.468)	(0.497)	(0.018)	(0.462)	(0.500)	(0.015)
# of panels	12.356	11.717	-0.639	15.043	13.702	-1.341***	15.797	14.201	-1.596***
	(7.341)	(7.644)	(0.451)	(8.355)	(8.062)	(0.402)	(8.526)	(8.245)	(0.324)
Size of panels	13.754	13.551	-0.204	17.235	15.900	-1.335**	18.345	16.905	-1.439**
	(9.051)	(9.135)	(0.554)	(10.55)	(10.35)	(0.513)	(12.10)	(14.34)	(0.538)
Observations	4957	553	5510	1102	1667	2769	1282	4894	6176

Notes: Table presents the solar PV investment statistics for subsidy applicants in years 2008, 2009 and 2010 separately for accepted and rejected households. We removed the top 5% outliers based on number of panels. Columns 3, 6 and 9 report the magnitude and statistical significance of the differences in variables between accepted and rejected applicants. Standard deviations are reported in parenthesis. * P<0.05. ** P<0.01. *** P<0.001

Table 3: Estimation Results for Solar Adoption and Panel Size

	(1) Solar adoption (Sub-sample)	(2) Solar adoption (Sub-sample)	(3) Solar adoption (Full-sample)	(4) Panel size (Sub-sample)	(5) Panel size (Sub-sample)	(6) Panel size (Full-sample)
Accepted	0.113***	0.118***	0.144***	0.201***	0.219***	0.332***
	(0.013)	(0.019)	(0.007)	(0.0369)	(0.0528)	(0.0231)
Household characteristics	No	Yes	No	No	Yes	No
Home characteristics	No	Yes	No	No	Yes	No
Observations	4,816	2,218	14,891	4,816	2,218	14,891

Notes: Table provides the average marginal effects calculated based on the logit estimation results for solar PV installation decision (columns 1, 2 and 3) and OLS estimation results for installed panel size (columns 4, 5 and 6). The dependent variable in columns 1, 2 and 3 is a binary variable that takes one if a household installs solar PV and zero otherwise. The dependent variable in columns 4, 5 and 6 is the log size of installed solar PV in m^2. This variable takes zero if the household does not install solar PV. Columns 1,2,4 and 5 report the results for the sub-sample for which the household-house characteristics information is available. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001.

Table 4: OLS Regression: Subsidy Effect on Timing

	(1) Timing (Sub-sample)	(2) Timing (Sub-sample)	(3) Timing (Full sample)
Accepted	-1.119***	-0.632***	-1.070***
	(0.0795)	(0.0924)	(0.0455)
Constant	3.284***	3.428***	3.261***
	(0.0868)	(0.593)	(0.0500)
Observations	3,031	1,383	8,754
R-squared	0.063	0.060	0.060
Household characteristics	No	Yes	No
Application year FE	Yes	Yes	Yes

Notes: mean coefficients; sd in parentheses * P<0.05. ** P<0.01. *** P<0.001. Sample includes all solar PV installing subsidy applicants. Timing is denoted as years in between the application year and the installation year.

Table 5: Marginal Subsidy Effects Solar Adoption: Heterogeneity Analysis

	Solar adoption
Accepted	0.644***
	(0.0960)
Accepted*Age_High	-0.122
	(0.131)
Age_High	0.291***
	(0.125)
Accepted*Wealth_High	-0.146
	(0.131)
Wealth_High	0.247***
	(0.119)
Constant	-0.0797
	(0.246)
Observations	4,816
Household Characteristics	YES

Notes: The dependent variable is a binary variable that takes one if a household installs solar PV and zero otherwise. The Table contains interaction terms for age and wealth, where low contains the bottom 50% and high the upper 50% of the sample based on the distribution of the observable characteristics. * P<0.05. ** P<0.01. *** P<0.001.

Table 6: D-i-D estimation Subsidy Effect on Electricity Consumption: 1-year and 5-year Effects

	(1) 1 year (Sub-sample)	(2) 1 year (Sub-sample)	(3) 1 year (Full-sample)	(4) 5 year (Sub-sample)	(5) 5 year (Sub-sample)	(6) 5 year (Full-sample)
Accepted*Post	-0.0374**	-0.0246	-0.0592***	-0.0393***	-0.0294**	-0.0810***
	(0.0171)	(0.0214)	(0.0144)	(0.0110)	(0.0138)	(0.00920)
Accepted	-0.00127	0.000260	-0.00573	-0.00127	0.000260	-0.00573
	(0.00865)	(0.0106)	(0.00666)	(0.00900)	(0.0111)	(0.00747)
Post	-0.0339*	-0.0643***	-0.0440***	-0.0322**	-0.0598***	-0.0243*
	(0.0193)	(0.0242)	(0.0163)	(0.0157)	(0.0195)	(0.0138)
Constant	8.145***	8.137***	8.262***	8.145***	8.137***	8.262***
	(0.0101)	(0.0128)	(0.0283)	(0.0105)	(0.0134)	(0.0317)
Observations	13,220	8,133	36,226	26,629	15,771	72,869
R-squared	0.005	0.011	0.005	0.029	0.065	0.065
Household characteristics	NO	YES	NO	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES

Notes: Mean coefficients; sd in parentheses * P<0.05. ** P<0.01. *** P<0.001. Dependent variable: log electricity consumption. Pre period: 3 years before the subsidy. Post period: 5 years after the subsidy. Period 0 (subsidy application year) is excluded from the analysis. 5% outliers in electricity consumption removed.

Table 7: D-i-D Estimation Subsidy Effect on Electricity Consumption: subsample analysis

	Age Low	Age High	Wealth Low	Wealth High
Accepted*Post	-0.0389**	-0.0392**	-0.0324**	-0.0455***
	(0.0151)	(0.0161)	(0.0160)	(0.0151)
Accepted	-0.00830	0.00672	-0.00127	-0.00275
	(0.0119	(0.0136	(0.0133)	(0.0122)
Post	-0.0300	-0.0313	-0.0196	-0.0427*
	(0.0217)	(0.0227)	(0.0231)	(0.0213)
Constant	8.177***	8.105***	8.123***	8.169
	(0.0140)	(0.0157)	(0.0150)	(0.0147)
Observations	13,117	13,512	13,273	13,356
R-squared	0.024	0.029	0.020	0.039
Household char.	NO	NO	NO	NO
Year FE	YES	YES	YES	YES

Notes: Mean coefficients; sd in parentheses * P<0.05. ** P<0.01. *** P<0.001. Dependent variable: log electricity consumption. Pre period: 3 years before the subsidy. Post period: 5 years after the subsidy. Period 0 (subsidy application year) is excluded from the analysis. 5% outliers in electricity consumption removed.

A Appendix for Online Publication

Table A.1: Logit Estimation Results for Application and Acceptance to Subsidy Program

	(1) Application	(2) Acceptance
Number of household members	0.145***	0.070
	(0.044)	(0.095)
Age of household head	-0.004	0.001
	(0.002)	(0.005)
Number of children	0.004	-0.084
	(0.050)	(0.106)
Number of elderly (>65)	-0.024	-0.098
	(0.032)	(0.065)
Number of females	-0.112***	-0.043
	(0.040)	(0.076)
Annual household income (€1000)	0.010***	-0.004
	(0.001)	(0.002)
Household wealth (€1000)	0.001***	0.000
	(0.000)	(0.000)
Education level		
Secondary school	0.536**	-0.076
	(0.216)	(0.430)
Vocational school	1.099***	0.053
	(0.190)	(0.379)
Higher vocational school	1.925***	0.211
	(0.190)	(0.377)
Bachelor degree	2.388***	-0.059
	(0.235)	(0.459)
Master/PhD degree	2.187***	0.330
	(0.194)	(0.384)
House size (m^2)	0.005***	-0.000
	(0.000)	(0.001)
Building construction year		
1930-1944	-0.253**	0.246
	(0.104)	(0.197)
1945-1959	-0.275**	0.202
	(0.109)	(0.210)
1960-1969	-0.390***	-0.0366
	(0.103)	(0.198)
1970-1979	-0.507***	0.112
	(0.0915)	(0.175)
1980-1989	-0.352***	0.088
	(0.090)	(0.173)
1990-1999	-0.138*	0.157
	(0.083)	(0.156)
2000+	0.136	0.214
	(0.092)	(0.170)
Dwelling type		
Corner house	1.504***	-0.0228
	(0.128)	(0.252)
Semi-detached house	1.679***	-0.038
	(0.131)	(0.255)
Between house	1.340***	0.015
	(0.120)	(0.240)
Detached house	2.020***	-0.017
	(0.132)	(0.251)
Constant	-7.319***	-0.110
	(0.257)	(0.515)
Number of observations	60,913	2,218

Notes: Table provides the logit estimation results for subsidy application decision (column 1) and subsidy provision after application (column 2). The dependent variable in column 1 is a binary variable that takes one if households applies for solar PV subsidy program and zero otherwise. The dependent variable in column 2 is a binary variable that takes one if the application for the subsidy program is accepted and zero otherwise for the applying households. The base category for education level is ”primary school”, for building construction period it is ”1900-1929” and for dwelling type it is ”apartment”. Standard errors are given in parentheses. * P<0.05. ** P<0.01. *** P<0.001.