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Incentives for the energy transition: Feed-in tariffs, rebates, or a hybrid design?

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Draft

Abstract

In this paper, I focus on monetary incentives for the energy transition in the residential sector. I study how different design choices affect the uptake of the technology, its siting, and therefore the cost-effectiveness of the decarbonization effort. I analyze two design choices in particular: (i) whether to pay the incentive per system installed (system-based incentive) or per kWh of electricity generated (output-based incentive), and (ii) whether to provide the incentive upfront or through payments delayed over a longer time frame. To assess these alternatives, I estimate the responsiveness of the demand for residential solar PV with respect to feed-in tariff (FIT) payments and with respect to installation costs in an empirical setting and look at how households trade off upfront installation cost and future FIT payments to obtain their implicit time discount rate. Finally, I calculate the cost per kWh generated and per emission reductions of the policy. In general, I find that households discount heavily future monetary benefits and have a high elasticity of demand to the incentive, so that a hybrid design that links the incentive to the output but is paid upfront would be more cost-effective than rebates and FITs. As budgetary and distributional concerns around green incentives are being discussed, rigorous assessments of these policies and their design is urgent. By learning from past experience we can improve future policy design in the energy sector and beyond.

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1 Introduction

A rich variety of policy tools has been used around the world to support the uptake of residential solar photovoltaic (PV) to help decarbonize the grid. While the literature has mainly focused on determining the optimal level of incentives and their schedule over time (Langer and Lemoine, 2018; van Benthem et al., 2008) or on identifying the impact of given policies (De Groote and Verboven, 2019; Pless and van Benthem, 2019; Hughes and Podolefsky, 2015), less has been done on how different design choices affect the uptake of the technology, the siting of the systems, and therefore the cost-effectiveness of the decarbonization effort. In this paper, I analyze two features that policymakers have to consider when designing an incentive for residential PV: (i) whether to pay per system installed (system-based incentive) or per electricity generated (output-based incentive), and (ii) whether to provide the incentive upfront or through payments delayed over time. Common incentive schemes such as rebates and feed-in tariffs (FITs) use opposite combinations of these features. Rebates decrease the upfront cost of installing a system, while a FIT pays the PV owner over time for the electricity that their system generates and transfers to the grid. Different combinations of these features are nevertheless possible, and, depending on the elasticity and time discounting parameters, might even have advantages over the existing policies. To assess this possibility, I set up a model of the household decision to install a PV system, and empirically estimate the parameters of interest using data from the UK FIT, a scheme with wide variations in the amount of incentives offered and other characteristics that make identification feasible.

I use a reduced-form specification to obtain the responsiveness of demand for residential PV with respect to the FIT payments and with respect to the installation cost. As upfront system-based incentives are effectively a discount on the installation cost, changing the sign of the latter provides the responsiveness to this type of incentives. To assess the choice of system-based or output-based incentives, I then construct an hypothetical payment scheme that is identical to the existing FIT in terms of schedule over time and frequency and duration of the payments, but pays a fixed amount per system rather than an output-dependent amount (set to be revenue neutral for comparability). Fitting the estimated parameters to this new variable and to the existing FIT, I predict the number and location of PV systems that would be installed under each design, net of the installations that would have occurred even without incentives. I also look at the role that covariates play in shaping the distribution of PV systems over the country. To isolate the role of the second feature of interest, I first look at how households trade off the upfront installation cost and the future FIT payments, obtaining the implicit time discount rate of households needed to compare the cost-effectiveness of upfront as opposed to periodic payments. Finally, I calculate the cost of the additional kWh generated (i.e., net of adoptions that would have occurred anyway) and the emission reductions.

The paper contributes to the economic literature on technology adoption, policy design, integration of renewables and the transition to a low-carbon economy and energy sector, and discusses practical policy alternatives to improve cost-effectiveness of renewables incentives, given budgetary pressure. As many incentive schemes for PVs are being phased out citing high cost and regressivity concerns, assessing the cost-effectiveness of these programs and ways to improve them is extremely relevant for policy and to inform future incentive designs.

A review of the key literature of interest with a focus on residential PV is included in Section 2. Section 3 presents the policy background and the data, while Section 4 introduces the theoretical framework of reference, on which the estimation approach in Section 5 is based. Section 6 discusses the results and Section 7 concludes with policy implications.

2 Main literature of reference

This research builds on a growing body of literature investigating the demand for residential solar PV systems and the effectiveness of incentives for their adoption, with applications mainly to the US, and most frequently California – De Groote and Verboven (2019) on

Flanders being a notable exception. The Flemish incentive scheme consists of a mix of output-based subsidies – similar to the UK scheme – and net metering – which is instead absent in the UK. In the US, support for residential solar systems is offered at the federal level through a tax credit for around 30% of the system cost. This is complemented by state-specific schemes, usually consisting of some form of subsidies and net metering. Under the California Solar Initiative (CSI) General Market Program, for example, residential solar PV owners can choose between an output-based subsidy called Performance Based Incentive paid monthly for 5 years, or an upfront lump-sum payment called Expected Performance-Based Buydown – with the vast majority choosing the latter (Hughes and Podolefsky, 2015). Although classified as a capacity-based subsidy, the Expected Performance-Based Buydown is actually adjusted depending on the expected generation of the solar array, calculated taking into account the characteristics of the system and the roof, as well as the solar insolation of the location where it is installed. In the paper, I draw comparisons between the results reported by the literature on the CSI and the results obtained here for the UK, and discuss the strengths and weaknesses of each policy design.

The literature looking at the microeconomics of residential solar subsidies may be classified according to two main approaches – reduced-form models and static estimates on one side, and dynamic decision-making problems employing structural models on the other.

Among the works in the first strand, Hughes and Podolefsky (2015) and Pless and van Benthem (2019) focus on the California Solar Initiative, using different empirical strategies. Hughes and Podolefsky (2015) exploit the difference in rebate amounts offered by different utilities to identify the effects of the rebate. As each utility serves a different territory, the boundaries of the catchment areas provide the discontinuity needed for identification. This is combined with time fixed effects and utility-specific time-varying fixed effects to control for unobservables that might bias the estimates. Allowing the elasticity parameter to vary, they find that a 0.10 USD (6%) increase in the rebate rate results in 20% more installations in the early periods of the policy, but this effects decreases to 8% in later times, corresponding to an average elasticity of -1.2. They estimate that the cost of the policy is 0.06 USD/kWh generated. Pless and van Benthem (2019) focus instead on the pass-through of the CSI rebate that is paid to the installers rather than to the end-users, and in their analysis they estimate a price elasticity of demand for solar panels of -0.85. Another important work to mention for its methodological as well as empirical contribution, is Gillingham and Tsvetanov (2019). The authors estimate the demand for residential PV in Connecticut, where systems are eligible for upfront rebates, and find a price elasticity of -0.65. Their estimation approach addresses three main issues that commonly arise in this type of analyses, namely the use of a count outcome variable with excess zeros, unobserved heterogeneity, and endogeneity of the main regressor - the price of the PV installation. They present two models that can be used in this situation – an instrumental variable (IV) Poisson model with fixed effects, and a IV Poisson-hurdle model with fixed effects – and show how to obtain a consistent estimator to estimate the parameters.

Among the structural models, again focusing on California, van Benthem et al. (2008) build an inter-temporal model to derive the optimal solar subsidy schedule in California, in the presence of environmental externalities and unappropriated learning-by-doing, and find that the existing incentive schemes in the state are very close to the model's optimum, while without learning-by-doing, environmental externalities alone cannot justify the high levels of subsidy. Burr (2016) analyses different types of incentives, concluding that upfront subsidies tend to result in more installations, but output-based subsidies are more efficient. She also notes that sub-optimal siting of residential PV results in high welfare cost. Langer and Lemoine (2018) estimate what the efficient subsidy schedule looks like when taking into account expectations about future subsidy and technology cost. Bollinger and Gillingham (2019) use a dynamic model of demand and supply to investigate the role of a rebate paid through the installers in fostering learning-by-doing in the industry. Allowing the elasticity to vary over time, they find values between -1.2 and -0.8, consistent with results from previous reduced-form analysis. In a recent working paper, Snashall-Woodhams (2019) uses highly disaggregated data on electricity consumption and estimates of solar generation potential at the rooftop level to model households' choice to adopt solar and compare the CSI with an optimally targeted subsidy. He finds that households discount heavily future benefits from solar, estimating an annual discount factor of about 82%. Finally, De Groote and Verboven (2019) use variation in subsidies for residential PV in the Flanders, Belgium, and a detailed structural model to identify the discount rate users appear to employ when choosing whether to install residential solar. As in the paper on California, they find the annual discount rate to be very high at 15% (equivalent to an annual discount factor of 0.86), and conclude that in cases in which the agents are myopic or discount heavily the future for other reasons, upfront subsidies are more cost-effective.

On the issue of siting and geographical distribution of residential solar, it is worth mentioning recent work by Sexton et al. (2018), estimating the effects of solar electricity generation on averted pollution damages and on grid congestion, and how they vary over the US territory. They find substantial heterogeneity and spillovers across states, and conclude that incentives could be made more efficient and more environmental benefits could be achieved by better linking the level of subsidies to the location-specific outcome.

3 Policy background and data

The empirical setting chosen to answer the research question is the UK FIT scheme for residential PV, which was in place between 2010 and 2019. When a household installed a PV system during this period, they were assigned a FIT rate per kWh generated and this rate is paid for 20 years, indexed for inflation. The reason for this choice of setting is that this is a purely output-based design, where households are paid periodically for each kWh generated in the period, no matter whether the electricity is then self-consumed or transferred into the grid, and with no net-metering (McKenna et al., 2018).[1] This simplifies the modeling

[1] While production and export to the grid are measured and rewarded separately for higher capacity bands, separate meters are not generally available in the residential sector and the policy simply assumes that 50%

and data requirement to isolate the effects of interest, and allows me to focus solely on the household decision to install a system without modelling the decisions of how much energy to consume and how much to export. The second reason for this choice is that the FIT rate changed multiple times every year, providing useful variation to identify the parameters and remove seasonality effects. Quoting the sustained decrease in capital costs of solar PVs as the main rationale, the FIT rate has in fact been repeatedly adjusted downward, from 43.3 in 2010 to 3.79 at the beginning of 2019.[2] It is to be noted that changes in the rate only affect new applicants, while nothing changes for households who have already installed.

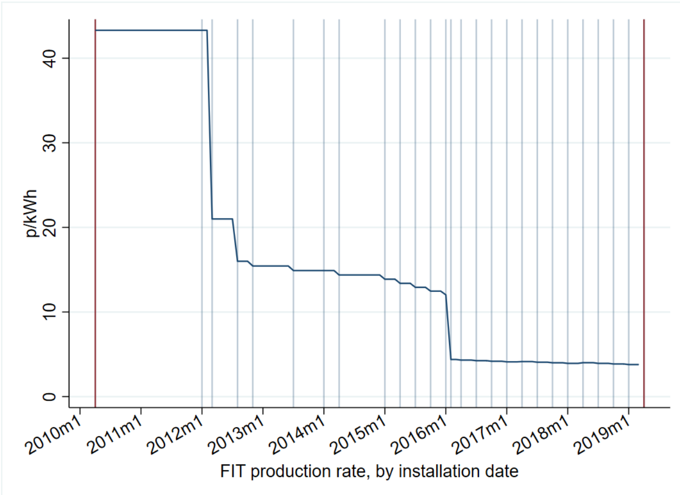
While the rate per kWh generated is fixed across the country at a given time (Figure 1.a), the actual FIT payments the household receives depend on how much their system generates, which is determined by the generation potential of the location where the system is installed and by contextual weather conditions (Figure 1.b; see also Section 4). The total amount of incentives offered, obtained as the product of the FIT rate and of the electricity generated, therefore varies both over time and space (Figure 1.c). As an example, a household that installs a system in the South-West in 2013 receives higher FIT payments than a household that installs at the same time in the North, because of the difference in solar irradiation, cloudy days and overall generation potential of the areas; at the same time their FIT payments will be lower than those of a household who installed a system in the same area but in 2011, because systems installed in earlier years receive a higher rate for each kWh generated.[3]

For the empirical analysis I compile a novel dataset from several sources. The unit of observation is the Middle-Layer Super Output Area (MSOA), a statistical construct developed within the UK census to ensure within-homogeneity and between-comparability of

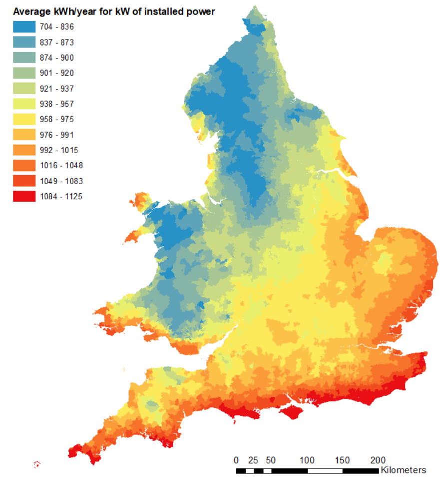
of the household generation is exported, effectively linking the payment only to the energy generated and abstracting from energy consumption decisions.

[2]The budget for the scheme comes from the general electricity bills of all energy suppliers' customers – as it is the case for other energy-related schemes in the country – and high costs and distributional equity concerns were cited as main arguments behind the closure of the scheme in 2019.While distributional issues are not covered in this paper, I refer to Grover and Daniels (2017) for a discussion on the UK, and Borenstein (2017) for California.

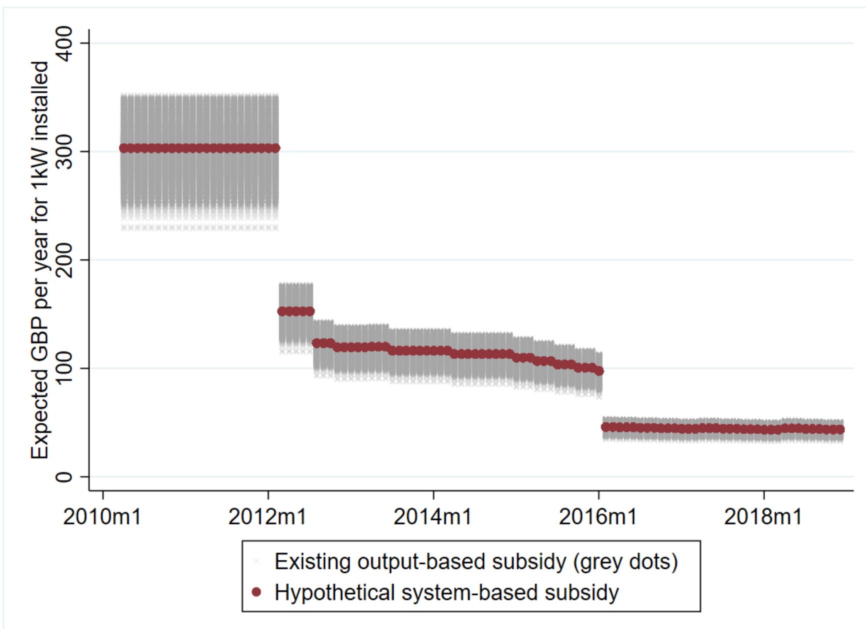
[3]Holding all other characteristics of the system, such as slope and orientation constant.



(a) FIT rate, for 0-4kW solar PV systems.



(b) Solar generation potential.



(c) Range of the expected annual FIT payments for 1kW of installed power (grey), which depends on date and location of installation. Hypothetical system-based incentive (red) used in the second part of the analysis to assess the siting consequences of output-based and system-based incentives.

Figure 1: Expected annual FIT payment and its components. Own calculation on Photovoltaic Geographical Information System (PVGIS) data and Ofgem data.

socio-demographic characteristics and comparable population size in each unit (2,000-6,000 households). The final dataset is a monthly panel of observations for the entire duration of the FIT program for the whole of England and Wales (7,194 MSOAs). The installation dates and locations of the residential PV systems come from the Office of Gas and Electricity Markets (Ofgem) and I use this information to count the number of new installations in each MSOA and in each month of the panel (Figure 4). I focus on systems that are classified as "domestic"[4] and with declared net capacity equal or less 4kW, which constitute 97% of the total residential installations. Systems in higher capacity bands require an authorization to be installed and are only eligible for a lower rate that follows a different schedule and changed at different time; for these reasons I exclude them from the analysis.

The expected annual FIT payment is obtained as the product of the expected electricity generation at the population-weighted centroid of an area (obtained from engineering estimates from the Photovoltaic Geographical Information System, PVGIS[5]) and the FIT rate in place at the time of installation (also from Ofgem). This is the same type of information that households looking into installing PV can find on the web or from installers and energy efficiency associations.[6] The average payment varies from 300 GBP per year per kW of installed capacity at the start of the scheme, to 120 GBP after various reforms in 2012, to only around 45 GBP after the reform in early 2016, with several adjustments in between, as shown in Figure 1.

I refer to the price paid to purchase and install a solar system as 'cost' of the installation, as I am framing the installation problem as an investment decision with a trade-off between

[4]The systems are classified as domestic, community, commercial, or industrial.

[5]Data were obtained from the European Commission Joint Research Centre in Ispra. Values are based on the PVGIS SARAH database. Details on the methodology and the dataset can be found in Huld and Amillo (2015) and Huld et al. (2012).

[6]Households can customize their estimate by providing the exact address and rooftop characteristics such as orientation, slope, and shading. As I do not have this level of information, I use the population-weighted centroid of the area to approximate the location and set the rest of the parameters to standard ideal settings of no shading, south-facing orientation, 35 degrees slope, and 14% system losses. I then multiply the generation estimates obtained by a factor of 0.7, to account for the fact that a substantial share of the households will not have ideal conditions for installation, such as a east-west orientation, a non-optimal slope, or shading from trees and nearby buildings.

costs and future revenues. Data on the cost of installing PV systems come from the Microgeneration Certification Scheme (MCS), which record the price paid by customers who install PV in the country (Figure 5) together with their location, date of installation, and system capacity. To obtain a value of the cost per kW of installed capacity at the area-month level, I use different approaches; on one side, I first calculate the cost per kW of installed capacity of the observed installations and then take the median and the mean for the area-month; on the other side, I first take the mean and median of the overall cost and of the installed capacity, and then obtain the ratio. Given the presence of outliers in the data, I use the median cost per kW for the main specification, while I use the remaining three measures for robustness checks. I then need to impute the values for all the area-month combinations where no installation was performed and no direct information on cost is therefore available. I repeat the same steps using the municipality-month as the aggregation unit, and use this municipality-level measure to replace the missing values; for the remaining missing observations, I construct the same measure at the region-level (Gillingham and Tsvetanov, 2019). This approach is sensible in this setting as installers compete over large areas and carry out installations even far from their headquarters.

Other covariates included as controls are average electricity consumption before the start of the FIT scheme, quantity of detached, semi-detached, terraced houses and apartment buildings, median house price, quantity of owner-occupied houses, number of residents in different socio-economic categories, employment information (number of residents working from home, working as homemakers, retired, and unemployed), resident origins (number of residents born in the UK, in the EU, and elsewhere), and surface area (a proxy for population density, as MSOAs are constructed to have comparable population size, the larger an area is the less dense and more rural it is). These variables come from the census, employment datasets from the office of national statistics, and various government departments. Due to the very low number of installations and lack of data on system costs in the first year of the policy and after the FIT reform and drastic cuts of 2016, I restrict my analysis to the period

April 2011-December 2016. Summary statistics are presented in Table 3 in the Appendix.

4 Theoretical framework

4.1 Single agent problem

In the context of small-scale electricity generation, it is becoming more and more common to refer to the owner of a system as a 'prosumer' to stress the change that these systems introduce in the relationship between the household and the energy they now not only consumes but also produces. As electricity producers, the households involved in the decision to adopt PV may therefore be modelled as profit-maximizing units, following the theory of the firm in microeconomics:

$$\max_{q_k=\{0,1\}} \Pi(q_k, \psi_k) = S_k(y_k(q_k, \psi_k)) - C_k(q_k) \tag{1}$$

that is, unit k chooses whether to adopt ($q_k = 1$) or not ($q_k = 0$) – or the capacity to install – in the same way a firm may choose to 'enter the market' or to make an investment, so to maximize their profits (Π). Profits are given by the difference between the revenues that can be obtained from the production of electricity (i.e. the incentive or subsidy S) and the cost, or investment price, required to install (C). In line with the information collected from in-depth interviews with UK prosumers,[7] the cost is assumed to be paid upfront and without taking loans – but the analysis can be easily adapted to accommodate instalments and loans. In the case of solar PV in the UK, the revenues correspond to the output-based FIT incentive and depends positively on the electricity generated by the system (y_k), which in turns depends positively on the decision to install (q_k) and on the solar potential of the location (ψ_k), capturing conditions such as weather and cloud coverage, as well as tilt and azimuth of the roof, and shading. This can be formally written as $\frac{\partial S_k^{out}(y_k)}{\partial y_k} > 0$ and

[7] In-depth interviews were conducted as part of the ENABLE EU project. More information on the project and the methodology may be found in Standal et al. (2018, 2020).

$\frac{\partial y_k(q_k,\psi_k)}{\partial \psi_k} > 0$.

As the UK incentive is purely output-based and does not depend on the amount of electricity consumed by the household,[8] I abstract from modeling the consumption side in this framework. Therefore:

$$\frac{\partial \Pi^{out}(q_k,\psi_k)}{\partial \psi_k} = \frac{\partial S_k^{out}(y_k(q_k,\psi_k))}{\partial \psi_k} - \frac{\partial C_k(q_k)}{\partial \psi_k} = \frac{\partial S_k^{out}(y_k(q_k,\psi_k))}{\partial y_k(q_k,\psi_k)} \frac{\partial y_k(q_k,\psi_k)}{\partial \psi_k} > 0$$

To understand how this scheme differs from a capacity-based incentive, consider that under the latter the incentive would only depend on the installation decision, i.e. $S^{cap} = S(q_k)$, and the solar generation potential parameter drops out of the profit formula, so that:

$$\frac{\partial \Pi^{cap}(q_k)}{\partial \psi_k} = \frac{\partial S_k^{cap}(q_k)}{\partial \psi_k} - \frac{\partial C_k(q_k)}{\partial \psi_k} = 0$$

That is, compared with capacity-based subsidies, output-based subsidies should trigger more installations in areas with higher solar potential. The difference between the two distribution should be larger the more variation in solar potential there is over the country (i.e. the larger $\frac{\partial y_k(q_k,\psi_k)}{\partial \psi_k}$ is), the higher the payment of an additional unit of electricity generation is ($\frac{\partial S_k^{out}(y_k(q_k,\psi_k))}{\partial y_k(q_k,\psi_k)}$), and the more responsive households are to the incentive.

Output-based incentives like the FIT are paid periodically – here I consider annually – in the case of the UK FIT for 20 years. The total incentive S_k is therefore the present value of the flow of annual payments s_k. Each payment is calculated as the product between the FIT rate per kWh and the total amount of electricity generated in the corresponding period. The latter is not a pre-determined amount but depends on several factors outside of the household's control, including the solar potential of the location and actual weather conditions. When considering whether to install, the actual generation is therefore unobservable by the agent, and they consider instead an 'expected outcome'.

[8]For example, the UK does not have any form of net metering, a scheme frequently used in other countries. More details on the policy background are presented in the next Section.

When the agent considers installing, the expected outcome is therefore the same in every year – as roof characteristics are fixed, there is no reason to expect systematic differences in the weather in one direction or the other between years, and the FIT rate per kWh generated is determined by the rate in place at the time of adoption and is held fixed throughout the 20 years.[9] The annual subsidy can therefore be considered as a constant annuity, calculated as the product of the expected annual generation (a random variable) times the FIT rate at the time of the installation (a constant):

$$s_{k,t}(y_{k,t}(q_{k,t=0},\psi_k)) = y_{k,t}(q_{k,t=0},\psi_k)\cdot \mathrm{FIT}_{t=0} \tag{2}$$

and taking the expectation at the time of the adoption decision:

$$\begin{aligned} E[s_{k,t}(y_{k,t}(q_{k,t=0},\psi_k)] &= E[y_{k,t}(q_{k,t=0},\psi_k)\cdot \mathrm{FIT}_{t=0}] && = \\ &= E[y_{k,t}(q_{k,t=0},\psi_k)]\cdot \mathrm{FIT}_{t=0} && = \\ &= s_k(\bar{y}_k(q_{k,t=0},\psi_k) && \forall t = 1,...,T \end{aligned} \tag{3}$$

The total subsidy is therefore the present value of an annuity over a finite period of time:

$$S_k(q_k) = \sum_{t=0}^{n} \frac{s_{k,t}(y_{k,t}(q_{k,t=0},\psi_k)}{(1+r)^t} = \frac{1-(1+r)^{-T}}{r}\ s_k(\bar{y}_k(q_{k,t=0})) = \rho\ s_k(\bar{y}_k(q_{k,t=0})) \tag{4}$$

where T is the number of years the subsidy is paid for (in this case 20 years), and r is the discount rate. I do not make any assumption on the discount rate but consider it as one of the parameters to be estimated. In the estimation section I therefore calculate the implicit discount rate derived from the inter-temporal trade-off between upfront costs and future subsidies.

As the government sets the FIT rates, households are 'incentive-takers' (equivalent to

[9] The rate is indexed to the Retail Price Index (RPI) and is therefore adjusted for inflation on a yearly basis. There is therefore no need for the household to take inflation into consideration in their decision.

price-takers firms in the theory of the firm). Similarly, households can be considered to be cost-takers, as their individual choices are unlikely to affect the investment cost (in this case the price of the PV system and its installation). To support the latter assumption, it is worth remembering that PV modules and inverters are mostly imported from abroad and their price is determined in the international market.

4.2 Aggregate demand

The dependent variable for the empirical analysis is $Q_{i,t}$, the count of new installations in a location i at a given time t, so from the single-agent problem, I aggregate as follows:

$$Q_{i,t} = \sum_{k \in i,t} q_k \tag{5}$$

Changes in the subsidies and in the installation price result in changes in the profitability of the investment, and therefore trigger adjustment responses in how many households decide to install, which can be captured by a total elasticity term:

$$\eta_\Pi = \frac{\Delta Q}{\Delta \Pi}\ \frac{\Pi}{Q} = \frac{\Delta Q}{Q}\ \frac{S - C}{\Delta S - \Delta C} = \frac{\eta_S\ \Delta S - \eta_C\ \Delta C}{\Delta S - \Delta C} \tag{6}$$

and substituting for the expression of S in equation 4:

$$\eta_\Pi = \frac{\eta_s\ \rho \Delta s - \eta_C\ \Delta C}{\rho \Delta s - \Delta C}$$

The parameters of interest in the estimation are therefore the partial elasticity of demand to changes in the annual incentive:

$$\eta_s = \frac{\text{\% change in \#installations}}{\text{\% change in subsidy}} = \frac{\Delta Q}{\Delta s}\ \frac{s}{Q} = \beta_s\ \frac{s}{Q} \tag{7}$$

and the partial elasticity to changes in the cost of purchasing and installing a PV systems:

$$\eta_C = \frac{\% \text{ change in } \#\text{installations}}{\% \text{ change in cost}} = \frac{\Delta Q}{\Delta C}\,\frac{C}{Q} = \beta_C\,\frac{C}{Q} \tag{8}$$

I assume that agents display a constant response to changes in the levels of subsidies and installation cost (β), and the elasticity therefore varies depending on the value of these variables and of the number of installations (Q). I obtain estimates of the β coefficients through a reduced-form regression analysis, and then calculate the elasticity at the means of the parameters.

Another parameter of interest is the discount rate r. It is possible to recover an implicit discount rate from the regression coefficients by imposing that agents respond in the same way to an increase (or decrease) in the total revenues S, as they respond to a decrease (or increase) of the same magnitude in the installation cost C (the same assumption is made implicitly in De Groote and Verboven, 2019). This implies that the only difference between changes in the annual subsidy and changes in the cost is that the former entails future cash flows that need to be discounted, while the latter is an upfront payment. Details of how the implicit discount rate is obtained are presented in Section 5, where the regression model is presented.

Within this framework, I consider the main decision for a household to be whether to install a PV system or not. I do not model the decision on the capacity, or size to be installed, as in the UK there is evidence that this is constrained by the available space on the roof and by the barrier of smaller FIT rates and authorization requirements for systems larger than 4kW. In fact, under the UK FIT scheme (which applies to solar PV system up to 5MW), only systems 0-4kW are eligible for the highest subsidy rate and do not require any authorization to be installed and connected to the grid, so that over 90% of the installations eligible for FIT in the UK (i.e. solar PV systems up to 5MW) have a declared net capacity smaller than 4kW. The size of the system is therefore implicitly constrained to a maximum of 4kW in order to obtain the highest FIT rate and avoid the bureaucracy of obtaining the authorization. Within the 0-4kW range, I assume that the size of the system depends exogenously on the rooftop space available and is uncorrelated to the solar potential of an area. UK prosumers interviewed by the author (Standal et al., 2018, 2020) often mentioned that the number of panels installed was constrained by the size of their roof. The analysis can nonetheless be easily extended to model the choice of the panel size, by considering a continuous q_k bounded at zero, rather than a dichotomous variable. In this case the aggregated demand $Q = \sum_k q_k$ would represent the installed capacity rather than the count of installations, and would be continuous, but still bounded at zero.

5 Estimation model

Based on the theoretical framework presented in Section 4, installing a solar PV system can be thought of as a firm entering a market, as households pay the upfront installation cost, and then receive revenues over time thanks to the FIT scheme. If households are profit-maximizing agents, the demand for PV is therefore driven by the size of the profit Π that could be made from the investment. I specify the probability of observing a given number of new installations $Q_{i,t}$ in MSOA i and in month t as a Poisson distribution:

$$Pr(Q_{i,t}|\lambda) = \frac{e^{-\lambda}\ \lambda^{Q_{i,t}}}{Q_{i,t}!} \quad \text{with } \lambda = \exp(\beta_0 + \beta_\Pi\ \Pi_{i,t} + \beta_X X_{i,t}). \tag{9}$$

where $X_{i,t}$ includes other indirect costs and benefits of installation outside of the installation cost and FIT scheme, such as changes in the value of the house and cheaper electricity. In fact, when the PV system is producing, households can use electricity for free given that the UK does not have net metering at the time of the study and the FIT payments for the residential sector are only linked to the amount the system generates. Households who spend more time at home during the day are better able to take advantage of the free electricity, and I therefore include controls for type of employment and work arrangements to control for this aspect, as well as baseline electricity consumption. Exploiting the property of the Poisson distribution, I obtain the following regression equation:

$$\mathbb{E}(Q_{i,t}) = \exp(\beta_0 + \beta_{\Pi}\Pi_{i,t} + \beta_X X_{i,t}). \tag{10}$$

The expression for the profit can be developed in terms of the present value of the total cash flow of FIT incentive $S_{i,t}$ and the installation cost $C_{i,t}$:

$$\Pi_{i,t} = S_{i,t} - C_{i,t} \tag{11}$$

Each annual FIT payment that constitutes S is the product between the FIT rate per kWh at the time of installation (a constant) and the total amount of electricity generated in the year (a random variable). Given the policy design, the latter mainly depends on factors outside of the household's control, such as the solar potential of the area, the characteristics of the roof, and the realization of weather events. As detailed in the theoretical framework in Section 4, in the decision-making stage households have to form expectations on the generation amount and therefore the FIT payment, and have no reason to expect different values in different years. Indicating the 'expected' annual FIT payment as $s_{i,t}$, I can rewrite the total revenues as a constant annuity paid over 20 years:

$$S_{i,t} = s_{i,t}\ \frac{1 - \frac{1}{(1+r)^{20}}}{r} \tag{12}$$

where r is the discount rate – one of my parameters of interest.

Equation (10) can then be rewritten as:

$$\mathbb{E}(Q_{i,t}) = \exp[\beta_0 + \beta_{\Pi}\,(S_{i,t} - C_{i,t}) + \beta_X X_{i,t}] = \exp\left[\beta_0 + \beta_{\Pi}\,\left(\frac{1 - \frac{1}{(1+r)^n}}{r}\ s_{i,t} - C_{i,t}\right) + \beta_X X_{i,t}\right] \tag{13}$$

and re-naming the β coefficients:

$$\begin{cases} \beta_s & = \beta_\Pi \left(\frac{1-\frac{1}{(1+r)^n}}{r} \right) \\ \beta_C & = -\beta_\Pi \end{cases} \tag{14}$$

I obtain the regression equation:

$$\mathbb{E}(Q_{i,t}) = \exp(\beta_0 + \beta_s s_{i,t} + \beta_C C_{i,t} + \beta_X X_{i,t}). \tag{15}$$

As a reminder, β_s is identified thanks to variation in the expected FIT payment $s_{i,t}$ over time – due to changes in the FIT rate – and over space – because the incentive is output-based and there is heterogeneity in the expected outcome at each location according to climatic and geographic conditions. Once $\hat{\beta}_s$ and $\hat{\beta}_C$ have been recovered, I calculate the implicit discount rate $\hat{r}$ by solving the two-equation system in two unknowns in equation (14).

5.1 Estimation challenges and estimator

To empirically estimate the demand for residential PV, I set up a Poisson regression model (Silva and Tenreyro, 2006, 2011; Wooldridge, 2010, Chapter 18) using the panel dataset I constructed, with the number of new installations in a MSOA in a month as the outcome. The first issue I address is the bunching in the number of monthly installations, which is not smooth but shows spikes in proximity of each incentive cut (Figure 4.a). This can be a symptom of short-term dynamics such as delayed or anticipated installations which might confound identification of long-term effects. To address this problem, I include in the regression indicators for the month before and the month after a rate change.[10]

To control for unobserved heterogeneity that may confound the estimates and seasonal effects, I introduce year, month of the year, and municipality[11] fixed effects. Events that

[10] As the rate is changed as often as every three months, I cannot include controls for months further away from the change.

[11] I use "municipality" to refer to the 348 lower-tier local authority units in England and Wales, that is

affect the whole country in a given period, or specific characteristics or local policies and institutions that make areas different from each other but are not observed in my dataset, would in fact bias the results of the analysis if not taken into consideration. I choose to use municipality fixed effect rather than individual areas fixed effect in the main specification for two reasons. First, municipalities are the administrative divisions corresponding to the local governments, and I expect differences in local institutions and policies – if any – to occur at this level, while MSOAs are statistical constructs and in general do not have any administrative meaning. Second, I am interested in estimating explicitly the role of the built environment and of socio-economic characteristics, and many of these covariates do not change over time, so that introducing fixed effects at the individual area level would not allow their identification. I nevertheless conduct robustness checks using individual areas fixed effects and municipality-by-year fixed effects to support my results.

To address endogeneity concerns such as measurement errors and omitted variable bias, I use an instrumental variable (IV) approach. This is common practice to account for the simultaneity problem when using the price of a good as a regressor for its demand, as price and quantity tend to affect each other. Moreover, the policymaker may decide to adjust the FIT depending on the demand for PV, which might introduce another source of endogeneity, although this is more likely to be based on macro trends over the country rather than on the localized demand I am interested in. In both cases there may also be concerns of measurement errors. In the case of the installation cost, this is due to the fact that I only observe the variable when a purchase does occur, and I need to impute the value for areas and months with no installations, as explained in the Data section. In the case of the FIT incentive, I rely on engineering estimates of the expected generation of a solar system placed at the population-weighted centroid of the area and under standardized conditions and this might introduce measurement error compared to more direct measures of the variable.

To predict the exogenous variations in PV system costs, I use two cost-shifters as instru-

unitary authorities, metropolitan districts, London boroughs and local authority districts.

ment. The first one is the monthly price index of Chinese PV modules in the international market (as in De Groote and Verboven, 2019). The second is the regional median hourly pay for "Electricians, electrical fitters" (4-digit Standard Occupational Classification), a proxy for installers' wage. To obtain a valid instrument, I regress this variable on the median general wage for the region to remove possible income effects, which would be correlated with the error term in the demand equation (as discussed in Gillingham and Tsvetanov, 2019). While the price index only varies over time, the wage data are disaggregated for each of the 10 regions of England and Wales, introducing some variations over space, although they are not available at the monthly level, but only yearly. For the FIT incentive, I use an old provisional schedule of the levels and timing of changes in the rate paid per kWh generated. This schedule was drafted in the early stages of the scheme but neither the size, nor the frequency, nor the timing of the changes were actually followed. This instrument only varies over time. Results for the first stage are presented in Table 4 in the Appendix and show positive correlation between the instruments and the corresponding instrumented variables. As diagnostics for weak identification, the tables with the second stage include the Cragg-Donald F-statistics; the values do not point toward a weak instrument problem. As a robustness check, I also present the results instrumenting only the main regressor of concern, – the installation cost – and results are very close (see Table 1 and in the Appendix Table 5).

To empirically estimate my parameters of interest, I use an estimator based on Gillingham and Tsvetanov (2019), which, as shown in their paper, is consistent for a Poisson model with endogenous regressors and fixed effects. The estimator is based on the control function approach. In the first stage, the endogenous regressors are regressed on the excluded and included instruments using a linear model with fixed effects to recover the residuals. In the second stage, a Poisson model is used to regress the number of installations on the main regressors, the estimated residuals from the previous stage, and the covariates and fixed effects. Standard errors are obtained by bootstrapping. Several robustness checks are performed with different model specifications, including linear and tobit models.

6 Results

Results from the main model specification are presented in Table 1.[12] While the raw *beta* coefficients are used in the next steps of the analysis, for the interpretation of what these results mean I calculate the elasticity at the mean for both the incentive payment and for the installation costs. Note that these two elements are both components of the price elasticity (as shown in Section 4), as both incentives and installation costs affect the net price a household is facing to acquire the good. I find an elasticity at the mean of 3.31 for the incentive and of -6.92 for the installation cost. The estimated elasticity parameters are high, pointing to the fact that households are highly responsive to monetary incentives that change the profitability of adopting the technology. To facilitate comparison with results from the literature on rebates and price elasticity in general, I re-estimate the model using the installation cost net of the present value of subsidies, using a 7% discount rate (as assumed in van Benthem et al., 2008) that take into consideration the opportunity cost of purchasing a solar PV system rather than investing the same amount in a financial instrument with a comparable risk profile. I then evaluate the elasticity at the mean, obtaining -0.71. This result is close to the estimate of -0.85 found using a dynamic structural model by Pless and van Benthem (2019) for the California rebate policy, and to the -0.65 found by Gillingham and Tsvetanov (2019) for Connecticut, using reduced-form.

If households are highly responsive to monetary incentives, then making the amount received proportional to the outcome generated should result in more installations in areas of the country with better generation potential. To assess the benefits of this feature compared to a system-based incentive, I consider an hypothetical alternative policy that pays a fixed amount per system throughout the country, rather than an amount proportional to the output, but still periodically. To make them comparable, I keep the timeline and scale of

[12] Robustness checks are presented in Tables 5 and tab:feivlinear in the Appendix.

Table 1: Second stage. Poisson regression model with fixed effects and IV (control function approach).

	FE IV Poisson PV count	FE IV Poisson PV count
FIT payment	0.0223***	0.0170***
	(0.001)	(0.000)
Install. cost	-0.00351***	-0.00383***
	(0.000)	(0.000)
Month before change	0.813***	0.779***
	(0.008)	(0.007)
Month after change	-0.198***	-0.225***
	(0.018)	(0.012)
Residuals of cost from 1st stage	0.00356***	0.00388***
	(0.000)	(0.000)
Residuals of FIT paym. from 1st stage	-0.0109***	
	(0.001)	
Covariates	Yes	Yes
TOWN fe	Yes	Yes
MONTH fe	Yes	Yes
YEAR fe	Yes	Yes
Endogenous regressors	PV cost; FIT payment	PV cost
Instruments	Chinese PV index Install.wage (resid.) Provisional FIT	Chinese PV index Install.wage (resid.)
N	484754	484754
pseudo R-sq	0.34	0.34
Cragg-Donald F	255.9	1242.1
Implict discount rate	15%	22%
Implict discount factor	87%	82%

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

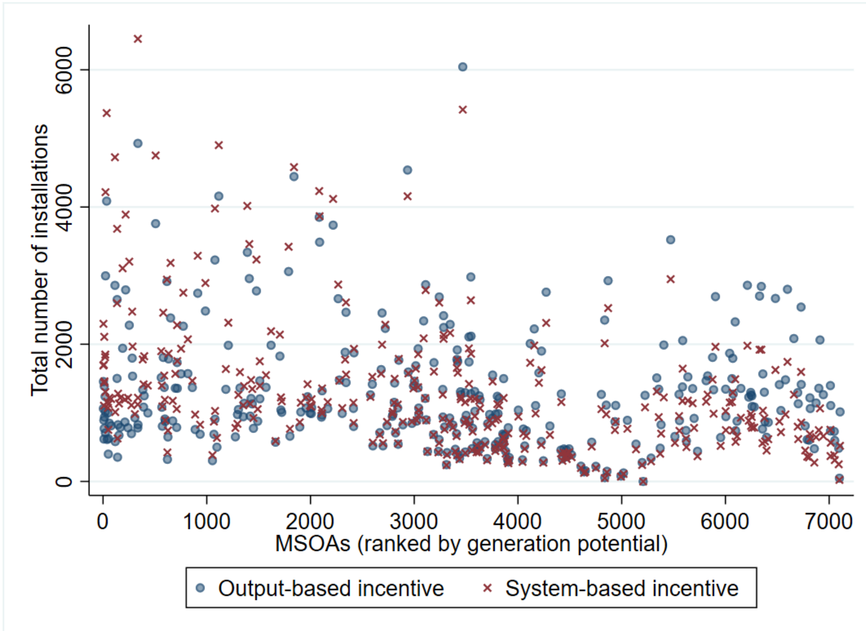


Figure 2: Siting of PV under different incentive designs. The x-axis shows the ranking of MSOAs according to their solar generation potential. The y-axis shows the total number of installations in each MSOA during the period under analysis.

changes as in the original FIT scheme, and select the amounts so that the predicted total number of installations in the period of analysis is the same as under the observed scheme. I then fit the estimated parameters using the observed output-based incentive and using the hypothetical system-based incentive, and predict the number of installations in each MSOA in each month. Analyzing the siting of the resulting installations against the generation potential of the area, I confirm that the latter ensures that systems are sited in locations with higher solar generation potential, with a correlation coefficient between the number of new installations in an area and the expected outcome of +0.09. Under the hypothetical system-based incentive, the correlation is not only lower, but change the sign to negative, with a coefficient of -0.12 (Figures 2 and 3). This results in less overall electricity generated and at a higher price.

To understand why the correlation between the siting of the PV and the generation potential of an area is so low, I look at the role that covariates play in fostering or hindering adoptions, and how they are distributed over the country and with respect to the expected outcome (Table 7). I find that the latter result is due to some contextual drivers of PV

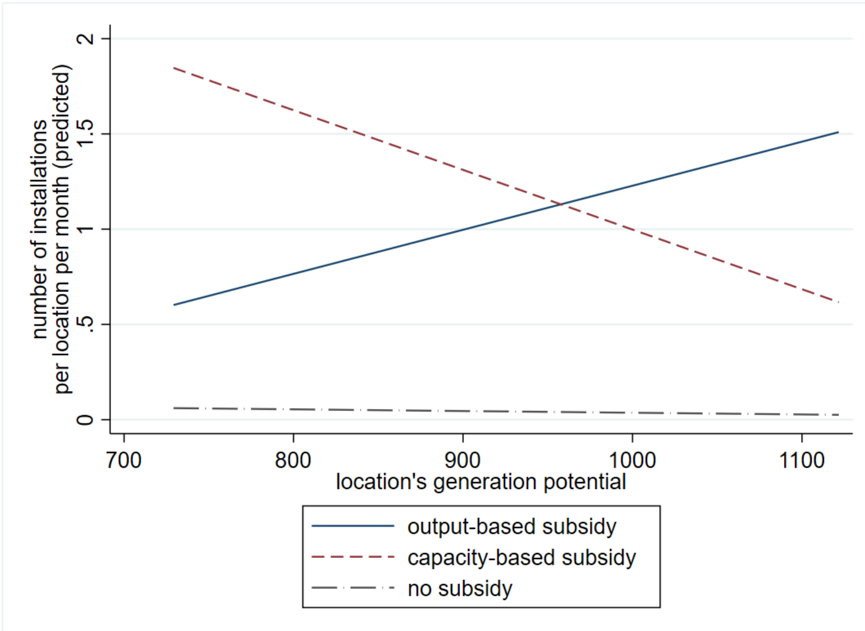


Figure 3: Correlation between installations and potential generation in the area in which they are installed, under the different incentive scenarios.

adoption, which favor installation but (at least in the UK) are more likely to occur in areas with low generation potential, for example low population density[13] (proxied by the size of the MSOA), high electricity consumption, owner-occupied houses, house prices[14], and number of people working from home. These covariates could be used to better target the incentives to achieve a more desirable siting.

In the next step, I assess the choice of paying upfront or delaying the payments over time. I obtain the implied annual discount rate using the estimated β coefficients to solve equation (14) for r. The implied rate is estimated to be high, at 15%, with a discount factor of 87%. These estimates are very close to results in the literature, such as the 82% discount factor on future electricity savings for California by Snashall-Woodhams (2019), and the 15% discount rate for FIT payments in Belgium estimated by De Groote and Verboven (2019).

[13]Graziano and Gillingham (2015) also find that population density has a negative effect on PV adoptions, which are more abundant in rural and sparse areas.

[14]Note that in the UK historical houses, such as listed buildings and buildings in conservation areas, have stringent regulation on what modifications can be made and require authorization for the installation of solar panels and other energy related measures (Hilber et al., 2019). Moreover, the aesthetics of the house is an important concern in the country, and many households oppose solar panels because they make the house look "ugly" and are afraid they might lower its value (Standal et al., 2020). These concerns are likely to affect higher-value houses.

While the cited papers use dynamic structural models and are therefore better suited than the reduced-form analysis of this paper to identify the parameter, it is reassuring that results are consistent, and contribute to the evidence that households considering whether to adopt PV 'behave as if' they discount heavily the future. It is worth remarking that this parameter can capture other behavioral features in addition to pure time preferences, so that it does not necessarily mean that agents are myopic. For example, it might capture time inconsistent discounting; mistakes in calculating the subsidies due to low financial or technical literacy; undervaluation due to uncertainty and risk aversion as future subsidies are not as certain as the upfront cost; default bias, as households might prefer to stick with their current energy setting rather than invest cognitive efforts in modifying it; unobserved search costs to obtain relevant information, or other transaction costs; or households might be afraid they will not be able to appropriate all of the subsidies, for example if they think they may move out of the house before the end of the 20 year period and be unable to capitalize the system in the house sale price. As long as the incentive provider can borrow at a lower rate, this level of discounting suggests that upfront payments – or even payments over a shorter time frame – would be more cost-effective than periodic payments spanning decades.

To discuss the cost-effectiveness of the UK FIT policy, I use some back-of-the-envelope calculations. I start by using the preferred specification to predict the number of installations that would have occurred even with no subsidies, to understand the additionality of the policy. In particular, I assume that the production rate is zero and only the export rate (which is close to the wholesale price of electricity) is paid for the electricity sold to the grid, estimated to be 50% of the total generation, as for the existing policy. Repeating the calculation assuming not even the export rate is offered result in even higher additionality. I refer to the marginal adopters as the 'policy-induced' installations, computed by subtracting the number of inframarginal adopters from the number of installations predicted for each subsidy scenario. I predict that without the subsidy, 13,136 installations would have happened anyway in the period under consideration, corresponding to about 5% of the predicted total under the existing scheme.[15] Nevertheless, the rents appropriated by these inframarginal adopters are even lower than this share, because compared to the marginal installations they tend to occur in later times, when the cost of installing and the FIT rate are lower, and in areas with lower solar generation potential. I estimate that the amount of subsidy paid out to these households is 3% of the total, suggesting that the scheme has a very high additionality and not many households would have adopted without incentives to do so.

By inducing more installations, the objective of the scheme is to decrease emissions from electricity generation in the country. I estimate that the installations of residential solar PV systems induced by the policy in the period 2011-2016 will have produced more than 45,300 GWh during their lifetime[16] This is roughly equivalent to 22.65 million metric tons of CO2-eq emission avoided, as compared to the case in which the same amount of electricity was generated using the energy mix the country had in 2010[17]. This is achieved with an expenditure of around 4 billion GBP in FIT payments over the 20 years each installation is eligible for support[18]. This is equivalent to approximately 179 GBP per metric ton of CO2-eq avoided, substantially more expensive than the California upfront rebate scheme, estimated at between 130 and 196 USD (95-143 GBP) by Hughes and Podolefsky (2015). In terms of electricity generated, I estimate a cost of the policy of 0.09 GBP per kWh, again substantially more expensive than the cost per kWh of the California CSI, estimated at 0.06 USD (0.04 GBP) in the same study. This difference can be explained by the fact that the California CSI consists of rebates on the upfront cost of the PV systems. In fact, when using the estimated implicit discount rate the cost of the policy drops to 0.05 GBP per kWh

[15] As a reference, the number of per capita installations predicted in absence of subsidies is higher to the number of installations in Norway, a country with almost no support scheme for solar as of 2016 Standal et al. (2020); in fact it is even larger, consistent with the better solar potential of the UK compared to Norway. This comparison suggests that the estimates are in a sensible range.

[16] Useful lifetime is assumed to be 30 years as in van Benthem et al. (2008) and in the pessimistic scenario of Frischknecht et al. (2015), although this assumption might be conservative, as the latter study considers 35 and 40 years in their realistic and optimistic scenario respectively.

[17] The carbon intensity of electricity generation in the UK in 2010 is estimated to be around 500 grams of CO2-equivalent per kWh (Staffell, 2017).

[18] Present value for policy costs are calculated using a 5% discount rate

generated and 98 GBP per metric ton of CO2-eq avoided, closer to the estimates for the upfront rebates in California. This suggests that a large part of the incentive goes to cover households' 'impatience', and that the cost of the policy could be lowered by providing the incentive upfront or in a shorter timeframe.

Even in this case, the policy remains expensive if considered only as a tool to correct environmental externalities; as a reference point the European Union Emissions Trading System (EU ETS) carbon market price has never been above 40 GBP[19] per metric ton of CO_2-eq avoided, and the estimates for the social cost of carbon (SCC) proposed in the Stern Review do not exceed 100 GBP (Stern, 2007). Yet, support for renewables provides additional benefits, including fostering innovation and learning-by-doing (Jaffe et al., 2005). In particular, van Benthem et al. (2008) find that when both environmental externalities and unappropriated learning-by-doing are taken into account, the incentive schemes in California are very close to the optimal incentive schedule.

7 Conclusions and policy implications

To conclude, the results of this paper suggest that an "hybrid" design with incentives provided upfront and in an amount that depends on the output potential would be a more cost-effective solution to increase clean energy generation than periodical FIT payments or upfront system-based rebates. Delaying incentives over time can make a policy very expensive if households have high rates of discount for future payments, which may result from present-oriented preferences, aversion to uncertainty, or even from inattention and low financial or technical literacy, with households struggling to calculate the returns of their investment. This result is likely generalizable to many contexts, as the literature provides evidence that these factors are indeed relevant for the uptake of residential solar PV in other countries and of new technologies in general. If households have high price elasticity for PV then incentives can effectively be used to shape siting decisions by linking the size of the payments to the

[19] As of February 2021.

outcome the policymaker is interested in, such as the output potential. I have shown that this is particularly important when contextual factors may be pushing toward undesirable siting. Understanding the role of these factors and their distribution over the territory are therefore important when choosing the policy design and could even be leveraged to target the policy.

As budgetary and distributional concerns are putting green incentive schemes under scrutiny, rigorous assessments of these policies and their design is critical and urgent. This paper contributes to these efforts, so that we can learn from past experiences and improve future policy design in the energy sector and beyond.

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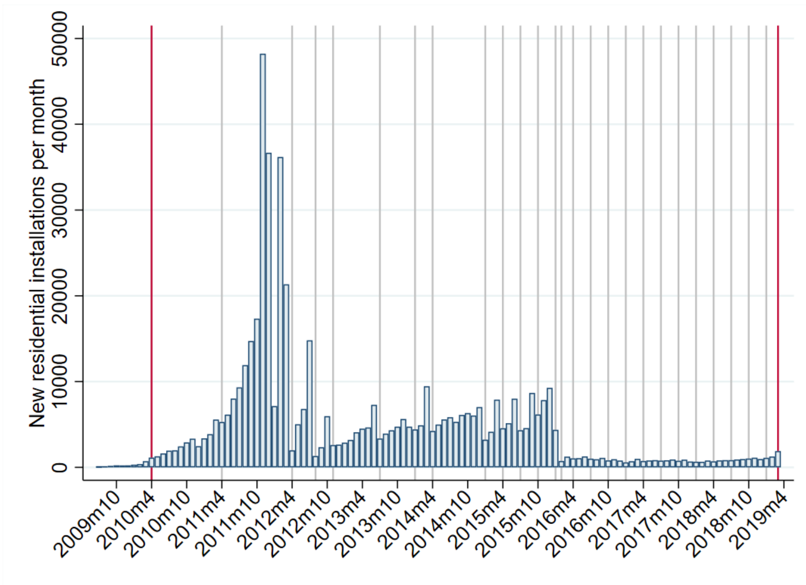
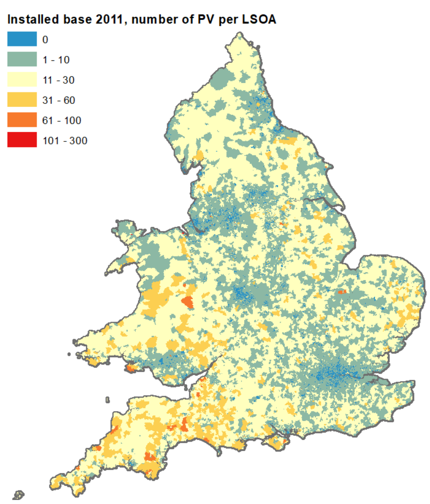
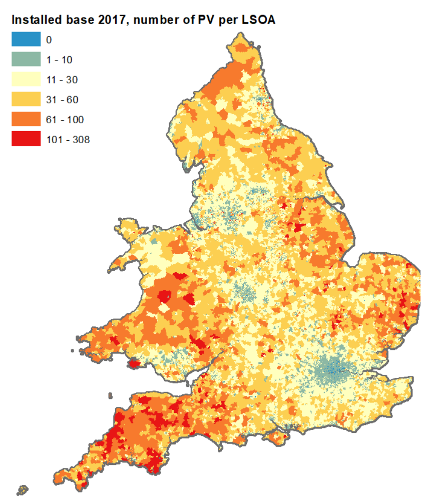
Appendix A Additional Figures



(a) Number of installation by month. The vertical lines show every time the FIT rate was changed. The red vertical lines mark the start and end of the policy.



(b) Installed base, 2011.



(c) Installed base, 2017.

Figure 4: Uptake of residential solar PV systems in England and Wales.

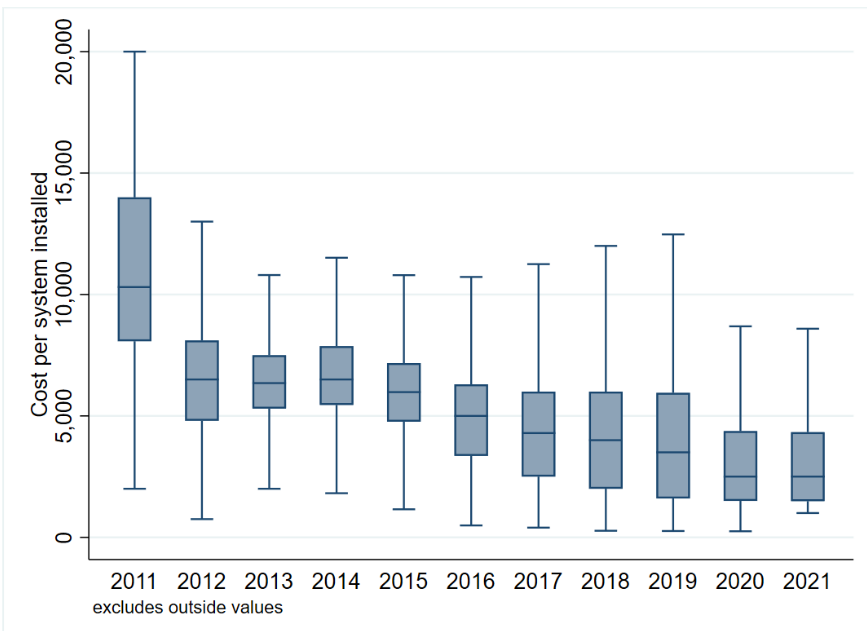


Figure 5: Trend in the cost of residential solar PV systems. Own elaboration on data from MCS.

Appendix B Additional Tables

Table 2: Back-of-the-envelope calculations of cost-effectiveness. Total capacity installed, total generation during panels lifetile, and cost of the policy per kW of installed capacity and per kWh generated, net of infra-marginal adoptions (in 2019 GBP).

Total MW of (net, or 'additional') capacity installed between 2011-2015	1,510 MW
Overall electricity generated assuming panel life is 30 years	45,307 GWh
Avoided emissions assuming carbon intensity of 500gCO2e/kWh	22.65mln mtCO2e
Total incentives for panels installed between 2011-2015, present value	
disc. rate = 0	6.20 billion GBP
disc. rate = 5%	4.05 billion GBP
Total incentive per kW of installed capacity, present value	
disc. rate = 0	4,104 GBP/kW
disc. rate = 5%	2,685 GBP/kW
Cost of policy per kWh generated	
disc. rate = 0	0.14 GBP/kWh
disc. rate = 5%	0.09 GBP/kWh
Cost of policy per mtCO2e avoided, present value	
disc. rate = 0	274 GBP/mtCO2e
disc. rate = 5%	179 GBP/mtCO2e

Table 3: Summary statistics.

	mean	sd	min	p25	p50	p75	max
PV count (new installations)	0.98	2.62	0	0	0	1	219
Expected FIT payment (GBP/year for 1kW installed)	132.02	76.15	33.87	101.68	113.98	127.22	352.18
FIT production rate (p/kWh)	17.5	11.5	4.2	12.9	14.9	16.0	43.3
FIT export rate (p/kWh)	4.4	.7	3.1	4.5	4.6	4.9	4.9
Provisional FIT rate (p/kWh)	35.2	5.2	27.5	30.2	36.3	39.6	43.3
Generation potential (kWh/year for a 1kW installed)	958	59	729	921	966	986	1122
Install. cost 1[1] (GBP for 1kW installed)	1914	599	800	1547	1762	2125	9972
Install. cost 2[2] (GBP for 1kW installed)	1972	597	800	1601	1837	2195	9972
Install. cost 3[3] (GBP for 1kW installed)	1889	626	226	1507	1722	2128	9669
Install. cost 4[4] (GBP for 1kW installed)	1971	596	226	1607	1840	2185	9669
Chinese PV module price index	.62	.17	.49	.54	.56	.58	1.32
Median installers wage (residuals)	.01	.41	-.82	-.27	-.07	.27	1.14
Median house price (GBP)	211530	137042	23375	126665	177833	250000	3500000
Av. electricity cons. 2010 (kWh/year)	3869	612	2389	3459	3737	4132	7779
MSOA surface area (km^2)	21.2	52.7	0.3	1.7	3.2	12.1	1128.1
# Owner-occupied houses	1912	692	24	1495	1930	2360	5182
# Flat (apt. buildings)	595	678	11	183	361	711	5725
# Terraced houses (townhouses)	814	557	17	393	683	1108	3710
# Semi-detached houses (duplex)	991	506	11	649	939	1285	3569
# Detached-houses	719	593	3	203	558	1147	3716
# Working from home	302	136	57	207	275	365	1167
# Housemakers	340	113	46	261	323	397	1123
# Retired	713	241	94	549	689	848	2445
# Unemployed	174	95	18	103	147	222	838
# SocioEc A[5]	179	112	16	96	153	236	868
# SocioEc B	263	179	24	136	220	339	1593
# SocioEc C	971	346	228	723	945	1184	2849
# SocioEc D	491	163	70	375	470	585	2384
# SocioEc E	366	154	81	260	337	439	1388
# SocioEc F	374	130	55	282	366	457	1105
# SocioEc G	611	199	121	467	598	736	1580
# SocioEc H	475	223	59	304	443	611	1513
# Born in UK	6596	1392	2082	5589	6487	7403	13536
# Born in EU	99	102	6	44	68	114	1363
# Born elsewhere	473	652	17	121	213	463	6143
# Months	69						
# Statistical areas	7,194						
# Municipalities	348						
Tot. observations	484,754						

Notes: [1] Cost in the MSOA-month is obtained as the median of the cost per kW of installed capacity from observed purchases. [2] ... average of the observed cost per kW installed. [3] ... ratio of the median observed system cost and the median capacity installed. [4] ... ratio of the average observed system cost and the average capacity installed. [5] Socio-economic group A (Large employers and higher managerial and administrative occupations), B (Higher professional occupations), C (Lower managerial, administrative and professional occupations), D (Intermediate occupations), E (Small employers and own account workers), F (Lower supervisory and technical occupations), G (Semi-routine occupations), and H (Routine occupations) from ONS (2005) capture household income and other socio-economic characteristics.

Table 4: First stage regressions. Install. cost 1 is the measure used in the main specification; the rest are robustness checks.

	Model with 2 endogenous regressors					Model with 1 endogenous regressor			
	FITpayment	Install.cost1	Install.cost2	Install.cost3	Install.cost4	Install.cost1	Install.cost 2	Install.cost3	Install.cost 4
Chinese PV index	105.3***	529.6***	589.9***	383.0***	570.0***	522.1***	522.6***	375.9***	477.4***
	(0.482)	(11.745)	(11.579)	(12.905)	(11.729)	(12.309)	(12.124)	(13.513)	(12.270)
Install.wage (residuals)	0.740***	57.07***	47.49***	71.91***	65.42***	56.49***	46.54***	71.43***	64.35***
	(0.086)	(2.099)	(2.070)	(2.307)	(2.097)	(2.104)	(2.072)	(2.310)	(2.097)
Provisional FIT rate	87.29***	304.8***	330.0***	249.8***	313.3***				
	(0.204)	(4.964)	(4.894)	(5.454)	(4.957)				
FIT payment						1.261***	1.732***	1.040***	1.823***
						(0.030)	(0.029)	(0.033)	(0.030)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TOWN fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MONTH fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	484754	484754	484754	484754	484754	484754	484754	484754	484754
R-sq	0.94	0.45	0.46	0.39	0.44	0.44	0.46	0.39	0.44
adj. R-sq	0.94	0.45	0.46	0.39	0.44	0.44	0.46	0.39	0.44

Standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: [1] Cost in the MSOA-month is obtained as the median of the cost per kW of installed capacity from observed purchases. [2] ... average of the observed cost per kW installed. [3] ... ratio of the median observed system cost and the median capacity installed. [4] ... ratio of the average observed system cost and the average capacity installed.

Table 5: Second stage regressions. Install. cost 1 is the measure used in the main specification; the rest are robustness checks. Poisson with fixed effects and endogenous variables (control function approach).

	FE IV Poisson with 2 endogenous regressors				FE IV Poisson with 1 endogenous regressor			
	PV count[1]	PV count[2]	PV count[3]	PV count[4]	PV count[1]	PV count[2]	PV count[3]	PV count[4]
FIT payment	0.0223***	0.0342***	0.00976***	0.0214***	0.0170***	0.0195***	0.0153***	0.0187***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Install. cost	-0.00351***	-0.00585***	-0.000577***	-0.00314***	-0.00383***	-0.00415***	-0.00354***	-0.00370***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Month before a change	0.813***	0.758***	0.770***	0.772***	0.779***	0.719***	0.803***	0.745***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
Month after a change	-0.198***	0.120***	-0.471***	-0.174***	-0.225***	-0.125***	-0.249***	-0.156***
	(0.018)	(0.022)	(0.016)	(0.018)	(0.012)	(0.013)	(0.013)	(0.013)
Residuals of cost from 1st stage	0.00356***	0.00586***	0.000624***	0.00314***	0.00388***	0.00417***	0.00359***	0.00371***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residuals of FIT paym. from 1st stage	-0.0109***	-0.0231***	0.00203***	-0.00998***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TOWN fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MONTH fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous regressors	PV cost					PV cost		
		FIT payment						
Instruments		Chinese PV index				Chinese PV index		
		Install.wage (resid.)				Install.wage (resid.)		
		Provisional FIT						
N	484754	484754	484754	484754	484754	484754	484754	484754
pseudo R-sq	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34
Cragg-Donald F	255.9	206.7	308.1	346.2	1242.1	1165.9	851.4	1208.6
Implicit discount rate	15%	16%	2%	14%	22%	21%	23%	19%
Implicit discount factor	87%	86%	98%	88%	82%	83%	81%	84%

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: [1] Cost in the MSOA-month is obtained as the median of the cost per kW of installed capacity from observed purchases. [2] ... average of the observed cost per kW installed. [3] ... ratio of the median observed system cost and the median capacity installed. [4] ... ratio of the average observed system cost and the average capacity installed.

Table 6: Second stage regressions. Install. cost 1 is the measure used in the main specification; the rest are robustness checks. Linear 2SLS (IV) with fixed effets.

	FE IV Linear with 2 endogenous regressors				FE IV Linear with 1 endogenous regressor			
	PV count[1]	PV count[2]	PV count[3]	PV count[4]	PV count[1]	PV count[2]	PV count[3]	PV count[4]
FIT payment	0.0351***	0.0578***	0.0117***	0.0336***	0.0343***	0.0418***	0.0277***	0.0377***
Install. cost	-0.00626***	-0.0111***	-0.000345*	-0.00563***	-0.0102***	-0.0114***	-0.00815***	-0.00937***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Month before a change	0.793***	0.727***	0.677***	0.722***	0.892***	0.752***	0.865***	0.772***
	(0.019)	(0.027)	(0.012)	(0.017)	(0.026)	(0.028)	(0.024)	(0.024)
Month after a change	0.327***	0.953***	-0.212***	0.369***	0.552***	0.848***	0.396***	0.684***
	(0.032)	(0.060)	(0.018)	(0.031)	(0.031)	(0.036)	(0.029)	(0.031)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TOWN fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MONTH fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous regressors	PV cost FIT payment				PV cost			
Instruments	Chinese PV index Install.wage (resid.) Provisional FIT				Chinese PV index Install.wage (resid.)			
N	484754	484754	484754	484754	484754	484754	484754	484754
Cragg-Donald F	255.9	206.7	308.1	346.2	1242.1	1165.9	851.4	1208.6
Implicit discount rate	17%	19%	NA	16%	30%	27%	29%	25%
Implicit discount factor	85%	84%	NA	86%	77%	79%	77%	80%

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: [1] Cost in the MSOA-month is obtained as the median of the cost per kW of installed capacity from observed purchases. [2] ... average of the observed cost per kW installed. [3] ... ratio of the median observed system cost and the median capacity installed. [4] ... ratio of the average observed system cost and the average capacity installed.

Table 7: Effects of covariates on solar PV uptake, partial correlation of covariates with the generation potential of locations, and resulting effect on siting. Socio-economic group A (Large employers and higher managerial and administrative occupations), B (Higher professional occupations), C (Lower managerial, administrative and professional occupations), D (Intermediate occupations), E (Small employers and own account workers), F (Lower supervisory and technical occupations), G (Semi-routine occupations), and H (Routine occupations) from ONS (2005) capture household income and other socio-economic characteristics.

	PV count (Poisson, IV)	Generation potential (partial correlations)	resulting effect on siting
Subsidy (GBP per 1kW installed)	0.0223*** (0.001)	0.106*** (0.001)	+
Install. cost (GBP per 1kW installed)	-0.00351*** (0.000)	-0.00610*** (0.000)	+
Electricity consumption in 2010	0.00006*** (0.000)	-0.00981*** (0.000)	−
MSOA surface area (km^2)	0.000694*** (0.000)	-0.230*** (0.003)	−
# Owner-occupied houses	0.000154*** (0.000)	-0.013*** (0.000)	−
Median house price	-0.000000408*** (0.000)	0.0000821*** (0.000)	−
Residents in socio-economic group A	-0.0004*** (0.000)	-0.285*** (0.002)	+
Residents in socio-economic group B	0.0003*** (0.000)	0.036*** (0.001)	+
Residents in socio-economic group C	-0.0001* (0.000)	0.052*** (0.001)	−
Residents in socio-economic group D	-0.0003*** (0.000)	0.0252*** (0.001)	−
Residents in socio-economic group E	-0.0001 (0.000)	0.127*** (0.001)	.
Residents in socio-economic group F	0.0000 (0.000)	0.090*** (0.002)	.
Residents in socio-economic group G	0.0000 (0.000)	0.082*** (0.001)	.
Residents in socio-economic group H	0.0006*** (0.000)	-0.092*** (0.001)	−
Flats	-0.0002*** (0.000)	0.000 (0.000)	.
Terraced houses	-0.0002*** (0.000)	-0.021*** (0.000)	+
Semi-detached houses	-0.0000 (0.000)	-0.038*** (0.001)	+
Detached houses	0.0003*** (0.000)	0.008*** (0.001)	+
Work from home	0.0006*** (0.000)	-0.104*** (0.002)	−
Homemaker	0.0005*** (0.000)	0.259*** (0.001)	+
Retired	-0.0001** (0.000)	-0.032*** (0.001)	+
Unemployed	-0.0004* (0.000)	-0.216*** (0.002)	+
Born in UK	0.0000 (0.000)	-0.010*** (0.000)	.
Born in EU	0.0003** (0.000)	0.119*** (0.002)	+
Born elswhere	-0.0002*** (0.000)	-0.027*** (0.000)	+
	plus f.e. and other controls		
N	484754	484754	
R^2		0.40	
adj. R^2		0.40	
pseudo R^2	0.34		

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$