BRINGING BREAKTHROUGH TECHNOLOGIES TO MARKET: EVIDENCE FROM RENEWABLE ENERGY FEED-IN-TARIFFS

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Credit market imperfections and positive externalities result in the under-provision of socially-beneficial technologies such as renewable energy. I examine whether the United Kingdom's renewable energy feed-in-tariff (FiT), which is a risk-reduction and price instrument, helped bring utility-scale solar energy to market. Exploiting the presence of bunching at the policy's eligibility threshold, I find that the FiT results in at least 2.3 GW of additional solar capacity between 2010-2015 (equal to one-fifth of the UK's total solar capacity today). The response is largely driven by new entry (94%), rather than inframarginal generators who downsize to become eligible. Dynamic bunching shows how entry rates increase in time periods when the tariff is higher and how bunching disappears once certain risk-reduction guarantees are removed. Simple value-for-money calculations reveal that it takes relatively low values of the social cost of carbon (£16-26/tCO2) for the FiT to represent a net gain.

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"If low carbon technologies are to play a substantial role in reducing carbon emissions in the coming decades, then it will be necessary to make them commercially available at scale in a timely manner." - Gross et al. (2018)

I. Introduction

Acute crises such as pandemics or climate change illustrate the value of breakthrough technologies such as vaccines, low-carbon energy and climate-smart infrastructure. These technologies can save lives and help avoid significant economic damage. However, they remain under-provided because of uncertainties leading to undiversifiable risk, incomplete information, positive externalities, and the irreversible nature of investments (Dixit and Pindyck 1994; Jaffe, Newell, Stavins 2005). Left unaddressed, these issues can slow down the scale and speed of the deployment of important technologies.

In this paper, I examine how to bring breakthrough technologies to market, focusing on the expanding clean energy, which is critical to achieve the United Kingdom's (UK) target of a zero-carbon power grid by 2035. Prior to 2010, the UK had no utility-scale solar on its grid.[1] Using a dataset of all renewable energy projects between 2010-2019, I empirically evaluate the extent to which the UK's feed-in-tariff (FiT), which provides renewable energy generators a fixed tariff for electricity sold to the grid,[2] incentivised entry and investment in commercial solar power.[3,4] The policy's eligibility threshold requires generators to be less than or equal to 5 MW in terms of installed capacity/size.[5] I exploit the presence of bunching at the eligibility threshold, variation in the guaranteed tariff level, and changes to the FiT's pre-accreditation process to demonstrate that the FiT had a significant and large impact on solar capacity growth in the UK, mainly via incentivizing new entry, in a relatively short span of time.

[1] Utility-scale solar is much larger than residential solar systems.

[2] The fixed tariff that generators receive is called the "export tariff" since the electricity produced is "exported" to the power grid.

[3] The UK FiT, in practice, embeds two very different policies: (i) a "generation rate" to support residential or very small-scale solar for self-consumption and (ii) an "export rate" for commercial utility-scale solar for grid export. This paper exclusively focuses on the latter which will be referred to as the "FiT".

[4] Although the FiT was available to many types of low-carbon technologies, I limit my attention to its effect on utility-scale solar energy for the grid. Onshore wind, anaerobic digestion, and small hydro plants were also eligible provided they adhered to the 5MW threshold. Combined heat and power had a separate eligibility threshold at 2kW.

[5] For context, a 5 MW solar project is about 20-25 acres in size i.e., the size of several football pitches combined.

To motivate why bunching occurs, I develop a simple model in which investment costs increase with the variance of expected returns. In each period, small price-taking solar firms operating in the power market choose how much to invest and whether to wait or enter today, with or without FiT support. Investments are irreversible. The value of entering with a FiT increases in the volatility of electricity prices and the degree to which the FiT serves as a subsidy.[6] The FiT reduces investment costs by shielding risk-averse investors from a gamble on price ("volatility effect") while potentially raising revenue when the tariff exceeds the expected market price for electricity ("subsidy effect").[7] The model predicts strategic bunching at the eligibility threshold which is driven by: (i) inframarginal generators that would have entered at larger capacities in the absence of the FiT but downsize to take advantage of it, and (ii) new generators that decide to enter thanks to the policy.

I find that relative to a no-FiT counterfactual, there are at least 43 times more commercial solar projects thanks to the FiT. Only 6% of projects are inframarginal and have strategically downsized (reflecting lost solar capacity). The remaining 94% are new entrants (reflecting additional solar capacity). On net, the FiT induces at least 2.3 GW of additional solar capacity over a period of five years, making it responsible for at least one-fifth of the UK's current total solar capacity.[8] This is a lower bound estimate as the impact of the FiT is only identified in the window around the eligibility threshold.

Furthermore, I utilize variation in the extent to which the FiT provided a subsidy in expectation to do dynamic bunching. In the early phase of the policy when the FiT is not a subsidy, there are still at least 27 times more solar projects and capacity relative to a no-FiT counterfactual, demonstrating how firms value the elimination of price volatility due to the fixed tariff. In the later phases of the scheme, when the FiT is a net subsidy, bunching grows to 41 times more projects and capacity. Finally, bunching disappears as the FiT's pre-accreditation scheme was removed, once again illustrating how firms value risk-reduction.[9]

[6] Note, it is also possible for the fixed tariff to be *below* the wholesale electricity price, in which case, the FiT caps revenues and is more like a tax.

[7] Another way through which the FiT can reduce revenue volatility includes ensuring that it is easier to sell units of power. For simplicity, I only focus on price volatility elimination but the model can also allow for risk reduction on quantity sold.

[8] Based on solar capacity figures from April 2022.

[9] Pre-accreditation guarantees what tariff level generators will receive prior to beginning construction. This is valuable as construction times for utility-scale projects can be significant (i.e., 1-3 years).

The distribution of project size becomes smooth in the absence of an effective FiT - a key assumption for causal identification.

To supplement my bunching analysis, I leverage the exogeneity of electricity prices to solar generators to estimate the marginal effect of a change in subsidy and price volatility on entry. Because the FiT offers a fixed tariff, exogenous fluctuations in the electricity price change the extent to which it is a subsidy while higher volatilities make it more valuable as it as a shield. I find that (i) a 1% increase in the FiT subsidy induces a 0.84% increase in solar entry and (ii) a 1% increase in wholesale electricity price volatility induces a 1.5% increase in entry under the FiT.

Did the FiT represent value for money? Equipped with lower-bound estimates from the bunching estimator on how much new solar capacity can be attributed to the FiT, I undertake a simple value-for-money calculation. I compare the benefit in terms of displaced carbon emissions against the cost of payments in excess of the market price. Even for relatively low values of the social cost of carbon (i.e., £16-26/tCO2) the FiT represents a net gain for society. For context, lower bound estimates of the social cost of carbon from the literature are £60 t/CO2 (Pindyck 2018).

This paper makes several contributions to the literature. First, it builds a simple model of solar project entry and investment, and highlights how FiTs operate through two distinct mechanisms: the subsidy channel and the volatility-reduction channel. It clarifies that FiTs are only subsidies insofar as the guaranteed tariff exceeds the wholesale market price for electricity. This is important since in many public discourses, FiTs are erroneously used interchangeably with subsidies. The model shows that it is possible to have a revenue-neutral FiT with a tariff that is equal to the expected wholesale price which can still produce benefits for generators.

Second, while the impact of carbon pricing has been widely investigated in the environmental economics literature (e.g. Martin et al. 2014, Aghion et al. 2016, Calel and Dechezleprêtre 2016, Andersson 2019, Leroutier 2022), the role of policies with risk-mitigating components is relatively overlooked (exceptions include Ryan 2022 who examines counterparty risk for solar procurement via power purchase agreements in India). This is an important area for research since credit market imperfections strongly affect clean

energy investments due to their relatively large upfront financing requirements and long time horizons.

Third, this paper provides novel causal estimates of the effects of FiTs on entry and investment in utility-scale solar. This is important since FiTs have been deployed widely around the world and are heavily debated in public discourses. Much of the existing empirical work focuses on residential FiTs (e.g. Grover 2013 and Germeshausen 2018), where the agents analysed are households as opposed to firms and, the installation size, required upfront investment, and project horizons are orders of magnitude smaller relative to utility-scale projects. This creates a very different economic environment and problem. Other work includes cross-country regressions on FiTs and share of renewable capacity which presents its own set of identification challenges (e.g. Jenner et al. 2013, Smith and Urpelainen 2014, Dijkgraaf et al. 2018).

Finally, drawing the distinction between residential and commercial FiTs is crucial because of the differences in how the schemes may be financed and designed, and how this in turn, influences for value-for-money. In UK government policy evaluations, value-for-money calculations do not distinguish between the residential FiT, which received an orders of magnitude higher tariff than the commercial FiT. This confounds the narrative, leading to many policymakers dismissing the FiT outright, even though, as this paper finds, the commercial FiT reflected relatively good value for money.

The rest of this paper is structured as follows: Section II explains the institutional context, Section III presents the theoretical framework, Section IV describes the data and descriptive results, Section V has the bunching estimation, Section VI reports the dose-response estimation, Section VII undertakes some value-for-money calculations and Section VIII concludes.

II. Institutional Context

A. Feed-in-Tariff Design

The UK aims to fully decarbonize its power sector by 2035 and reach net-zero emissions by 2050. Achieving this will require a diversified portfolio of clean energy generation. The

government implemented the FiT in April 2010 to help achieve these goals. The scheme was phased out by April 2019.

The UK FiT provides a fixed price for electricity sold to the grid by a renewable energy generator which is less than or equal to 5 MW in size. This fixed rate is called the "export tariff" which is assured via a pre-accreditation process prior to project construction. The FiT contract is valid for 20 years. The FiT is available to solar photovoltaics, wind turbines, hydro, anaerobic digestion, and micro combined heat & power (which has a different eligibility threshold). I will focus on the policy's impact on solar energy.

During the first half of the FiT's implementation period, it was the one of the main risk hedging instruments on the market. Corporate PPAs for solar energy were extremely scarce as were insurance products (see Figure 1; Speer, Mendelsohn and Cory 2010).

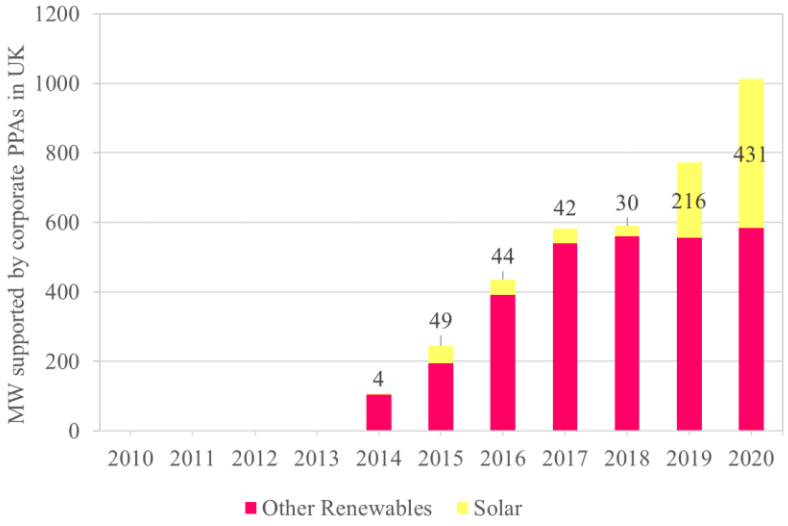


FIGURE 1. POWER PURCHASE AGREEMENTS IN THE UK

Notes: RESource 2022

The FiT also supports households and small commercial enterprises that wish to generate low-carbon electricity for self-consumption (rather than export to the grid).[10] Such entities are provided a separate tariff and supported installations are much smaller. I do not study this aspect of the policy, which has been analysed by other papers (e.g. Grover 2013). I focus exclusively on how the FiT affects commercial solar generators whose installations are orders of magnitude bigger than any home system (e.g. my main empirical analysis takes place in a window around 5 MW).

Electricity retailers must make payments to accredited FiT generators at the specified export tariff. The extent to which the export tariff exceeds the wholesale electricity price reflects the cost, which is passed onto to consumers through bills. While FiTs are often referred to as subsidies, they are only subsidies when the export tariff is above the wholesale electricity price. In the early years of the FiT, it was not a subsidy since the export tariff was below the market price for electricity (see Figure 2). While the FiT always eliminates price volatility, it is only sometimes a subsidy. This variation will be exploited in the dynamic bunching estimator (Section V.D.)

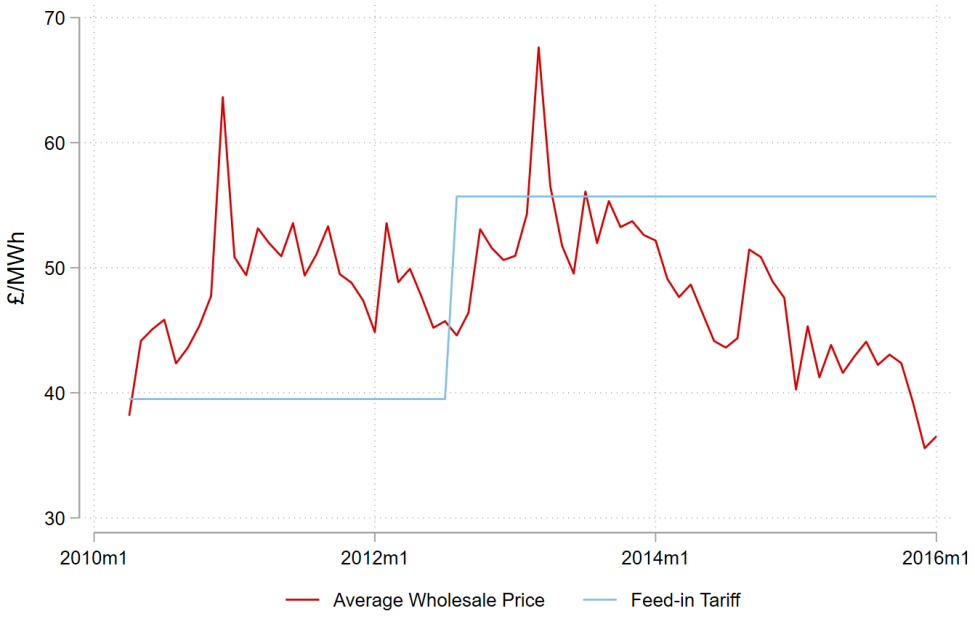


FIGURE 2. THE EXPORT TARIFF AND THE AVERAGE MONTHLY WHOLESALE ELECTRICITY PRICE

B. Background on Solar

Although solar panels are significantly more commonplace today, they were regarded as expensive, uncertain and risky technologies back when the UK FiT was announced in 2010. Solar panel costs were substantially higher in 2010 (Figure A.1 in Appendix H) and this brought into question the financial viability of the technology. The very first set of

commercial, utility-scale solar projects in the UK were FiT-accredited. There were no commercial solar projects prior to the policy.

Why might solar projects require risk-hedging instruments? Like other infrastructure and energy projects, investors looking at utility-scale solar farms must contend with long project horizons (>20 years), highly capital-intensive projects, volatile wholesale electricity prices, uncertainties in the due diligence and permitting process, and unpredictable output due to changing weather conditions (Figure 3). In the early-days of commercial solar in the UK, there was fundamental uncertainty over whether the technology could even be profitable at such latitudes. These factors affected the cost of capital which made up a significant portion of overall project costs (Steffen 2020).

"Project finance" is commonly used for renewable energy. A separate corporate entity or special purpose vehicle is established. There is typically no recourse to the parent corporation's balance sheet or credit worthiness, and the only collateral available to financiers is the renewable energy asset and its expected future cash flows (Steffen 2018). A scan of investor guidance documents reveals how in the early-days of solar, an "offtake agreement" was a pre-requisite for projects to get any sort of financing (Groobey, Pierce, Faber and Broome 2010).[10] Such offtake agreements could take the form long-term power purchase agreements (if available), or indeed, feed-in-tariffs. This reflected investors' uncertainty about whether merchant projects (i.e. those with no policy support) could even generate revenues.

Higher project risk translated into higher required returns and a higher cost of capital (Polzin et al. 2019). The cost of financing was significantly lower once an offtake agreement with a credible counterparty was present.[11] This motivates this paper's question about the role of credit market imperfections in the commercialisation of early-stage technology, and how risk-reduction instruments can mitigate some of the issues created by market failures related to information and finance.

[10] Such an agreement would ensure that there would be a stream of future cashflows

[11] Based on author's interviews with anonymous renewable energy generators, Aurora Energy Ltd., and experts at the UK's Low Carbon Contracts Company.

Stage of Project	Associated risks	Risk management approach
Planning & permitting	Delays, ownership disputes, legal and consulting costs	Local partners, legal due diligence, community involvement
Construction	Construction delays, cost over-runs, accidents	Insurance, over-run penalties, completion guarantees
Operating	Volume risk due to weather variations	Resource modelling, weather insurance
Operating	Technology risk & maintenance costs	Long-term maintenance & operation (M&O) contract, insurance
Operating	Electricity price volatility	Long-term PPAs; structured forward sales; pooling with other projects; FiTs, CfDs etc.
Operating	Policy risk	Hedging strategies, policy risk insurance, opting for long-term contracts
Operating	Counter-party risk	Investment-grade counter-parties, export credit, insurance, ring-fenced revenues, offshore accounts
Decommissioning	Ability to re-power, renewal of permits, land remediation costs	Reserve accounts

FIGURE 3. TYPES OF RISK

Notes: Adapted from Liebreich (2005)

III. Theoretical Framework

I develop a simple partial equilibrium framework which explains generators' incentives to enter, wait and strategically downsize. It details how generators respond to changes in price volatility and the FiT's expected subsidy level. The primary motivation for my theoretical framework is to set up the intuition for why and when bunching takes place.

A. The Model

The Environment — Solar generators are price-takers,[12] have zero marginal cost,[13] and decide on installed capacity (q_i) which determines their variable output (ηq_i), where η represents the capacity factor and i represents the generator. The capacity factor denotes the ratio of actual electricity output over the theoretical maximum. For solar energy, this ratio captures the impact of weather variability on realised generation.

[12] Renewable energy generators' electricity production is driven by exogenous weather conditions and cannot be strategically manipulated. Moreover, solar, which is the object of this paper's empirical analysis, accounted for only 4.3% of total electricity generation in 2020 (BEIS 2020).

[13] Marginal costs are zero for renewable energy generators because their "fuel input" e.g. sunshine and wind is freely available. In practice there are some very minimal variable costs linked to grid fees and maintenance but these can be ignored for modelling purposes.

Generators cannot manipulate the quantity of electricity they produce as this depends on exogenous weather conditions. They can, however, select their installed capacity, which determines their maximum possible electricity output in optimum weather conditions. In line with other literature, I assume generators know their own capacity factor (e.g. Kellogg 2014).[14]

The wholesale electricity price that generators face is volatile, $p_t \sim F(\mu_p, \sigma_p)$. Each generator has its project in a unique location which is associated with site-specific cost-shocks, $\chi_{it} \sim G(\mu_\chi, \sigma_\chi)$.[15] Fixed costs ($I_{it}$) are irreversible and financed by borrowing. I assume $I_{it} = (1 + \sigma_p)(1 + \chi_{it})\alpha_t q_i$ where α_t represents the cost per unit of installed capacity. The multiplicative functional form captures how price volatility and site-specific cost shocks affect each unit of installed capacity. For example, if the terrain is challenging, then mounting each panel will become more expensive, or if the project is risky, then each dollar borrowed will be at a higher cost of capital relative to a less risky project. For expositional simplicity and without loss of generality, I model I_{it} as a one-off fixed cost, though in practice it will be a flow of payments over time (e.g. interest payments on project financing).

The impact of σ_p on investment costs represents the cost of capital channel that is empirically documented for renewable energy projects where higher compensation is required for riskier investments (e.g., Byoun et al. 2013, Steffen 2018, Polzin et al. 2019). This assumption can also be conceptualised in terms of investors having risk aversion or a mean-variance utility function.[16] I assume risk cannot be fully diversified away because of uncertainty over the probability distribution of such risks or incomplete information (as is expected for new/early-stage technologies).

Firm Choice — In each period, generators decide whether to invest with or without policy or wait. This choice is represented by the maximum of the value of waiting (V_t^w), the value of investing today with a FiT (V_t^{FiT}) and the value of investing today without any policies i.e. as a "merchant project" (V_t^I) (see Equation 1):

[14] This is akin to allowing generators to have access to reasonable weather predictions of the medium run that can provide an indication of what the expected capacity factor for a given project and location may be.

[15] These costs depend on factors such as topography, distance from grid, land licensing costs, costs of due diligence requirements by the local council, chosen technology etc.

[16] This is standard CAPM models where the Sharpe ratio describes how much excess return investors need for larger standard deviations

(1) $$\max\{V_t^w, V_t^{FiT}, V_t^I\}$$

The discount rate is $\beta = \frac{1}{1+r}$ where r is the risk-free interest rate and $\beta \in (0,1)$. The value of waiting is given by Equation 2, where E_t is the expectations operator.

(2) $$\max_q V_t^w = \beta\{E_t V_{t+1}^w, E_t V_{t+1}^{FiT}, E_t V_{t+1}^I\}$$

Generators observe wholesale prices and period cost shocks, and assess whether these values lie above/below their expected values. If the value of entering today is less than the expected value of entering in the future, a generator will choose to wait.

The value of investing today with a FiT is given by Equation 3, where $\bar{p}$ represents the export tariff guaranteed under the FiT, q^f represents the optimal quantity of installed capacity, and $\bar{q}$ represents the FiT eligibility threshold.[17] The generator selects its project size subject to the FiT constraint.

(3) $$\max_q V_t^{FiT} = \bar{p}\eta q_i^f + \sum_{s=1}^{\infty} \beta^s (\bar{p}\eta q_i^f) - (1+\chi_{it})\alpha_t q_i^f \quad s.t. \quad q_i^f \leq \bar{q}$$

The value of investing today without any policy support is given by Equation 4, where q^I represents the optimal quantity of installed capacity with no policy. Note that a generator can enter at $q \leq \bar{q}$ and choose to not opt for the FiT.

(4) $$\max_q V_t^I = p_t \eta q_i^I + \eta q_i^I (\sum_{s=1}^{\infty} \beta^s E_t p_{t+s}) - (1+\chi_{it})(1+\sigma_p)\alpha_t q_i^I$$

Assuming a firm decides to invest in period t, its choice between investing with a FiT versus going merchant depends on whether $R_t \geq 0$, where $R_t \equiv V_t^{FiT} - V_t^I$ is defined below.

(5) $$R_t \equiv \left(\bar{p} q_i^f - p_t q_i^I\right) + \left(\frac{\bar{p} q_i^f - \mu_p q_i^I}{1-\beta}\right) - \frac{\alpha(1+\chi_{it})}{\eta}\left(q_i^f - (1+\sigma_p) q_i^I\right)$$

[17] For analytical ease I assume an infinite lifetime for each project. Adding a fixed time horizon T would merely scale the entry decisions for generators. Given my primary interest is the conditions under which a firm finds it optimal to bunch, this would not introduce a meaningful effect.

Differentiating Equation 5 with respect to price volatility, the export tariff, and the FiT installed capacity threshold illustrates how the preference for entering today with a FiT versus without it changes in these parameters. We can see that higher price volatility and a higher export tariff favour entry with a FiT ($\frac{\partial R}{\partial \sigma_p} > 0$, $\frac{\partial R}{\partial \bar{p}} > 0$), while a higher expected wholesale electricity price favours entry without a FiT ($\frac{\partial R}{\partial \mu_p} < 0$). This is intuitive since a FiT caps the upside of potentially very high market rates for electricity.

The value of waiting is solved recursively (see Appendix A). With a FiT, it is the maximum of (i) the discounted profit given the average electricity price and average cost shock, and (ii) the discounted profit given the FiT tariff and average cost shock. If there is no FiT, it is simply (i).

B. Model Predictions

Impact on Timing of Entry — To see how a FiT can induce more timely investment and entry, consider the following: as σ_p increases, holding all else constant, the value of entering with a FiT today will increase relative to the value of entering with no policy or waiting. This is because:

- $\frac{\partial V_t^I}{\partial \sigma_p} < 0$ as implied by Equation 4 and,
- $\frac{\partial V_t^W}{\partial \sigma_p} < 0$ as shown in Appendix B.

If the export tariff is at least equal to the average wholesale electricity price ($\bar{p} \geq \mu_p$), then in expectation, the value of entering with a FiT today will equal or exceed the value of investing with no policy or the value of waiting. In other words, without a FiT, as σ_p increases, both V_t^I and V_t^W fall. But with a FiT, as σ_p increases, V_t^W falls while V_t^{FiT} remains the same. A more formal exposition is presented in Appendix B, but the key message is that a FiT with a well-priced tariff (i.e. at least equal to the expected wholesale electricity price) can incentivise timely entry.

Bunching Behaviour — The model predicts that some generators that initially planned to install $\bar{q} + \Delta$ worth of capacity without policy support will revise their plans and re-locate to the FiT threshold, $\bar{q}$. These are the *inframarginal generators* as they would have entered even

without the FiT. The bunching upper bound, Δ, for which the generator is indifferent between downsizing and being at a higher capacity is obtained by setting V_t^{FiT} equal to V_t^I and solving for Δ:

$$\Delta = \bar{q}\left(\frac{p^F - \widehat{p_t}}{\widehat{p_t}}\right) - \frac{\alpha(1+\chi_{it})}{\eta}\left(q_i^f - (1+\sigma_p)q_i^I\right) \quad (6)$$

where $p^F \equiv \frac{\bar{p}}{1-\beta}$ and $\widehat{p_t} \equiv p_t + \beta\frac{\mu_p}{1-\beta}$. The value of Δ at which generators are indifferent between being at their capacity or downsizing to benefit from the FiT increases with the monetary benefits of the FiT and decreases with its costs (Equation 6). Δ is empirically important as it will define the area over which we will observe strategic downsizing (i.e., the "intensive margin" response). Since $\frac{\partial\Delta}{\partial\sigma_p} > 0$, we know that as volatility increases, generators will make bigger reductions in size to strategically benefit from the FiT. There is also an *extensive margin* response to the FiT, where for certain generators $V_t^W > V_t^I$ pre-FiT[18] but post-FiT, $V_t^{FiT} > V_t^W > V_t^I$. This will induce new entry. Empirically, using a bunching estimator we will determine the extent to which the UK FiT resulted in strategic downsizing on the intensive margin versus new entry, for different assumed values of Δ.

This partial equilibrium model does not consider the distortionary effects of volatility reduction on overall market outcomes. If FiT projects comprised a large share of the market, such distortions would be important to study. However, in my context, solar is < 2% of the market in terms of installed capacity, and FiT-accredited solar is less than half of all solar. Therefore, the size of these general equilibrium effects is likely to be very small. To explore how FiTs would affect firm incentives for later-stage technologies with higher market shares, one would need to relax assumptions related to price-taking and use a general equilibrium framework to better study the impacts on overall market outcomes.

[18] where, as shown in the appendix, in the absence of a FiT, $V_t^W = \beta\widehat{V}^I$

IV. Data & Descriptive Statistics

A. Data

The Renewable Energy Planning Database managed by the UK Department for Business, Energy & Industrial Strategy keeps a record of all commercial renewable energy projects as they move through the planning system. This database has detailed information on the project name, size, geo-location, status, types of policy support, among other variables. There are 2,481 unique commercial solar projects in the from 2010-2019. The median and the mode for project size is 5 MW, while the mean is 9.3 MW. Out of all solar project proposals, the status of 1,900 is known.[19] Out of these 84% have successfully entered the market while the rest have had their planning permit rejected or have chosen to exit before construction. The total number of clean energy projects across all technologies is 6,624. For the analysis, I assume a project "enters" when it applies for planning permission – this is the earliest date in the dataset. However, to ensure the results reflect actual added capacity, I filter out projects that subsequently backed-out or were denied permission.

Data on electricity prices at 30-minute frequencies is collected from Aurora Energy. The UK power market does not have regional variation in electricity prices and the grid functions as one market. The electricity prices that are relevant to solar energy are those that occur during daylight hours. To construct the appropriate wholesale electricity price variable, I use daily sunrise and sunset times to filter out night-time prices. [20] Using these "sunshine prices", I construct the average daily electricity price that solar generators would be exposed to. This is aggregated up further to construct monthly averages. I also use 30-minute daylight prices to calculate monthly volatility as relevant to solar generators.

Data on solar panel costs is from Bloomberg New Energy Finance and NREL.

[19] Projects labelled as unknown have applied for a permit but have not yet started construction, therefore it is unclear if they will be cancelled or will go ahead.

[20] In my time period, solar plus battery technology is highly limited, therefore it is safe to assume that the vast majority of solar generators only sell power during daylight hours. In the future, as battery penetration increases, solar generators may be able to sell much more power at night.

B. Descriptive Evidence

Between 2010-2019, nearly 1,600 commercial solar generators successfully entered the energy market, adding 12.5 GW of new capacity. The UK solar industry's beginning coincides with the introduction of the FiT in 2010 (Figure 4). Prior to 2010, there were no commercial solar projects in the UK.

Many factors may explain why solar technology diffused in the UK, such as the reduction in solar panel costs, favourable macroeconomic conditions, and public demand for clean energy. However, trends suggest that the FiT may have played a large role. For example, when the FiT export rate was increased by a third in 2012, there was a significant acceleration in entry. Similarly, in October 2015, when the FiT "pre-accreditation" was removed, entry rates plummeted and growth in solar capacity also fell (see Figure 5). The jagged structure of the plot reflects seasonality as each winter, the number of new solar projects falls, likely due to diminished sentiments, and every summer it peaks, due to stronger sentiments on the prospects of a technology that relies on sunshine.

The pre-accreditation process ensures that generators larger than 50 kW receive a guaranteed tariff level before beginning construction. This guarantee plays an important role because construction can take time and without pre-accreditation, generators could find themselves in a situation where by the time are ready to operate, the export tariff has fallen and the project is consequently, no longer favourable.

The decision to remove pre-accreditation was driven by a budgetary shock: capacity factors for offshore wind, which was supported by a different policy, turned out to be higher than predicted, and consequently offshore wind started eating into the overall budget. Despite the opposition generators had towards removing pre-accreditation, such a change was made anyway (DECC 2015b). An event study plot, which is presented in the spirit of descriptive evidence, illustrates how prior to the removal of the pre-accreditation process, there was an anticipatory increase in entry rates (see Appendix C).

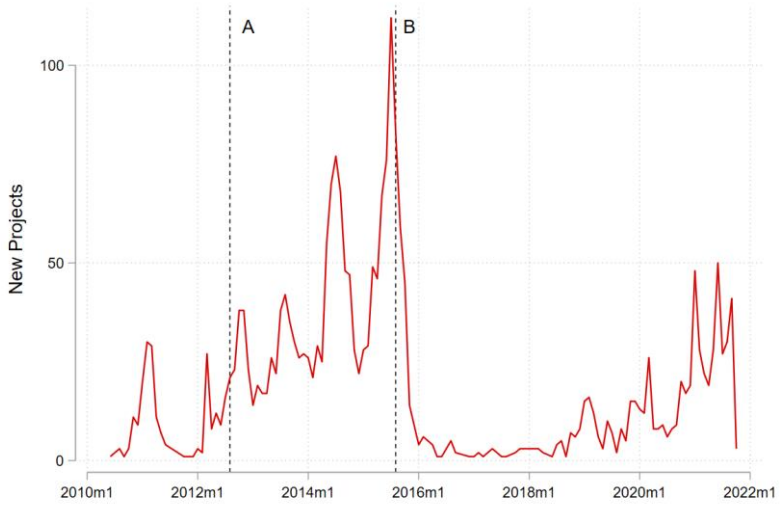


FIGURE 4. NEW COMMERCIAL SOLAR PROJECTS IN THE UK

Notes: The project entry date corresponds to when planning permission was sought. Projects that are denied planning permits are not shown to ensure only actual new capacity is reflected.

Solar project proposals start rebounding in 2018 but never returned to previous with-FiT levels. Plans to phaseout the FiT by the end of 2019 were clear and entry from 2020 onwards, reflects solar projects with no policy support.

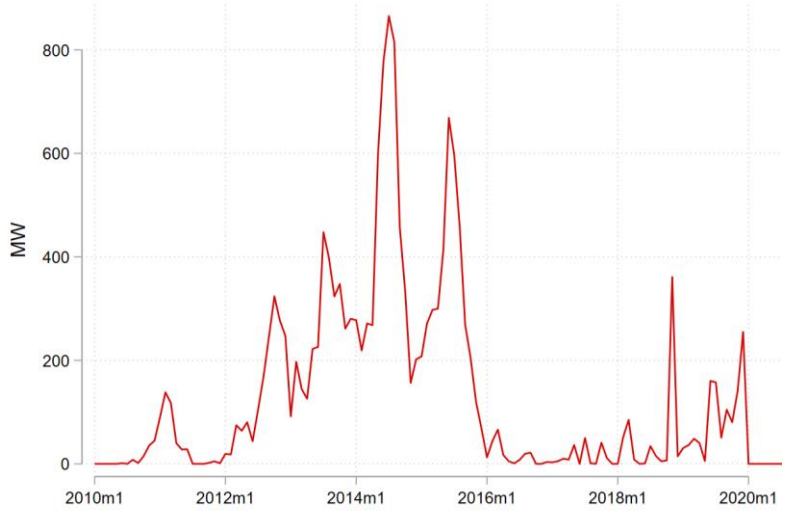


FIGURE 5. MONTHLY NEW SOLAR CAPACITY IN THE UK

V. Bunching Estimation

A. Empirical Strategy

The FiT creates a sharp discontinuity at 5 MW (i.e., a "notch") where generators below the threshold are eligible for the fixed tariff while those above the threshold are subject to fluctuating wholesale electricity prices. I exploit this discontinuity to estimate the impact of the FiT on entry and investment in commercial solar. Investment is proxied using project size, since larger projects require higher levels of investment.

Recall from the theoretical framework that firms can either wait, enter as a merchant project (i.e., with no policy support) or enter with a FiT. The bunching estimation will disentangle how much of the observed effect is driven by those who switch from waiting to entering with a FiT (i.e. new entry/extensive margin response) versus those who switch from entering as a merchant at higher capacities to downsizing and entering with a FiT (i.e. inframarginal/intensive margin response). While new entry results in solar capacity additions which is helpful for decarbonisation, strategic downsizing reflects lost solar capacity and support to inframarginal generators, which is inefficient.

There is a third potential behavioural response which is upsizing by generators who would have entered as merchant projects at lower capacities but who decide to scale-up to 5 MW thanks to enhanced profitability due to the FiT. However, I do not find evidence of this (see Appendix D). Consequently, the main results will only consider bunching from the right of the notch.

The bunching estimation is as follows:

$$(8) \qquad c_j = \sum_{i=0}^{n} \gamma_i (q_j)^i + \sum_{r \in N} \rho_r \cdot 1[q_r] + \sum_{i=q-}^{q+} \psi_i \cdot 1[q_j = i] + v_j$$

where c_j is the number of generators in bin j (each bin represents 0.1 MW increments of capacity), q_j is the installed capacity, n is the order of the polynomial , $[q-, q+]$ is the excluded range, and N is the set of round numbers (r) excluding the FiT eligibility threshold at 5 and including 2.5 and 1.5, where there is a tendency to bunch which is not driven by discontinuous incentives but rather the salience of certain numbers (i.e. natural reference points). The counterfactual distribution is defined as the predicted values from the regression

in Equation 8 omitting the contribution of the dummies around the notch (third term) but keeping the contribution of round-number dummies (second term) (Kleven and Waseem 2013).

The idea of the bunching estimation is to create a local no-FiT counterfactual and compare to the with-FiT observed data to determine how much "excess mass" there is at the notch due to the policy (Figure 6). To determine what proportion of this excess mass is due to strategic downsizing, the "missing mass" is calculated. This is the difference between the no-FiT counterfactual and the with-FiT observed data. The amount of new entry is the difference between the excess mass and the missing mass.

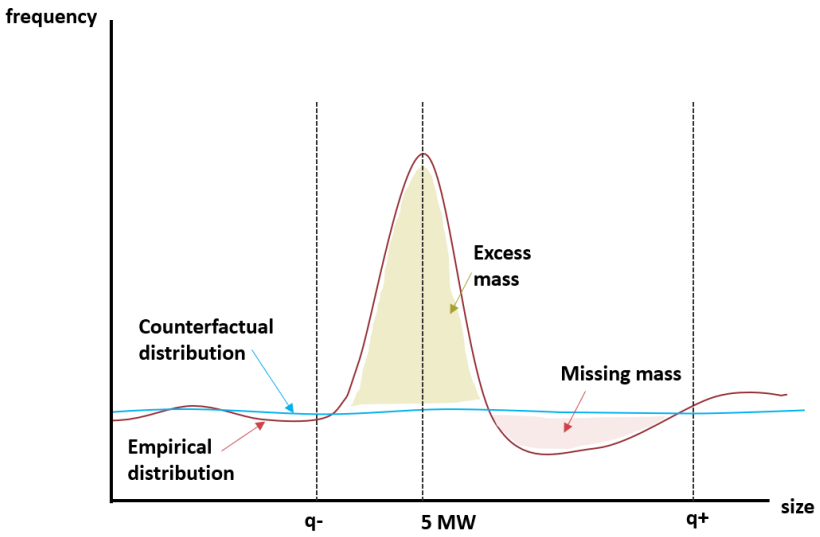


FIGURE 6. SCHEMATIC OF BUNCHING ESTIMATION

Deciding appropriate values for [$q-$, $q+$] is subjective[21]: $q+$ reflects our expectation of the upper bound from where generators will strategically downsize, while $q-$ is 5 MW since generators who downsize have no incentive to go below this value. In practice, I find $q- =$ 4.9 since many firms seem to mistakenly think the eligibility criterion is a strict inequality. In the baseline specification, I assume $q+ = 6.5$ MW. This choice is informed by a series of robustness tests that find there is no evidence for strategic downsizing beyond 6.5 MW. Using values of $q+ >$ 6.5 MW results in a negative missing mass, which is not compatible with downsizing (see Robustness Tests 1-3 in Appendix D).

[21] In settings where the response is almost entirely on the intensive margin i.e., due to strategic downsizing, the value of $q+$ is found by equating the missing mass towards the right of the notch to the excess mass under the notch. However, in my setting this is not possible since there is a large extensive margin response.

Adjustment costs (i.e. optimisation frictions) can attenuate the amount of bunching and create a downward bias in the estimate of how much firms respond to discontinuous incentives (Chetty et al. 2011). In my setting, this is not a large concern since projects are "paper proposals" where adjustment costs related to revising installed capacity plans are relatively low, and there is high salience around where these discontinuities occur since the agents are firms rather than individuals.

B. Identification Assumptions & Caveats

Identification via a bunching estimator requires that there are no other discontinuities at 5 MW apart from those created by the FiT. In other words, the no-FiT counterfactual distribution is smooth (Kleven 2016). I validate this assumption by checking the empirical distribution of solar project size post-2016, when the FiT was highly diluted/no longer effective. There is no observable bunching anymore (e.g. see Figure 9 and Item 3 in Appendix E). There is however, another discontinuity at 5 MW created by the Renewables Obligation (RO) scheme that helps renewable energy generators > 5 MW secure buyers for their energy. However, the planned closure of this scheme was announced in 2011 and there is no bunching above 5 MW, which would be expected if this scheme were influencing firms' decisions. Kleven (2016) also highlights how in the case of notches, behavioural responses can be very spread out. Sensitivity analyses with respect to the order of the polynomial and the excluded range show that results are very stable across alternative specifications (see Appendix D).

Since observations below the notch still benefit from the FiT but are used to create a "no-FiT" counterfactual, it is very likely that the results obtained are a lower-bound. An alternative is to estimate the counterfactual only using observations towards the right of the notch (i.e., those projects that are truly in a no-FiT world). However, this brings its own set of extrapolation challenges since larger projects may have different economic characteristics to small ones. It also results in the loss of statistical power due to dropping observations. Therefore, I choose to over-estimate the level of the counterfactual distribution, and produce a lower-bound estimate of entry and capacity additions with a FiT.

Additionally, one cannot rule out the possibility that the FiT makes 5 MW some sort of reference point. If this is the case, then "bunching confounds the incentive effect with a reference point effect" (Kleven 2016). I compare bunching across different time periods where the 5 MW reference point is the same but the extent to which the FiT is a subsidy changes. I see 1.5x more bunching when the fixed tariff is higher, confirming that holding constant any reference point effects, firms are responding to changes in the characteristics of the FiT policy.

Finally, I assume the marginal solar project does not influence prices in the power market. If one additional solar project affected prices in the power market, this would influence the expected revenues of the next solar project. This would mean decisions would not only take into account the financial incentives created by the 5 MW discontinuity but also include expectations of how other solar generators would react to it. This would confound our interpretation of the effect of the discontinuity. However, in my empirical setting, it is reasonable to assume a single 5 MW solar project does not influence prices in the power market. For context, the size of the UK power market is about 50,000 - 100,000 MW of installed capacity during my time period, making a single 5 MW project like a small drop in the ocean.

C. Main Results

This section presents the results from estimating Equation 8, where the exclusion zone is [$q- = 4.9$ $q+ = 6.5$], capacity bins are defined in terms of increments of 0.1 MW and a 4^{th}-order polynomial is used.[22] In the bunching results, B represents the number of projects at the notch, M is the number of projects strategically downsize, and B-M represents the number of projects that entered. The polynomial choice is represented by p while the multiple of excess mass due to the FiT relative to no-FiT is given by b (Figure 7).

As Figure 7 shows, there is a significant and very large bunching response at the FiT threshold. Around 6% of projects strategically downsize. The remaining 94% are new entrants. This shows how the FiT's effect is largely on the extensive margin: that is, it "created the market" by incentivising large amounts of entry and new capacity in

[22] Results with lower and higher order polynomials are reported in Appendix d. However, visually one can see that the data outside the notch is relatively flat, making it unlikely that higher order polynomials are needed.

commercial, utility-scale solar energy. Only a small minority of projects manipulate size in response to the policy. Taking into account the capacity lost from strategic downsizing, I find there are *at least* 43 times more projects thanks to the FiT, leading to net capacity additions worth 2.3 GW (equal to one-fifth of all installed solar capacity in 2021 in the UK).[23] In terms of absolute numbers, there are 490 new projects due to the FiT (for context, the total number of solar projects from 2010-2019 is 2,500).

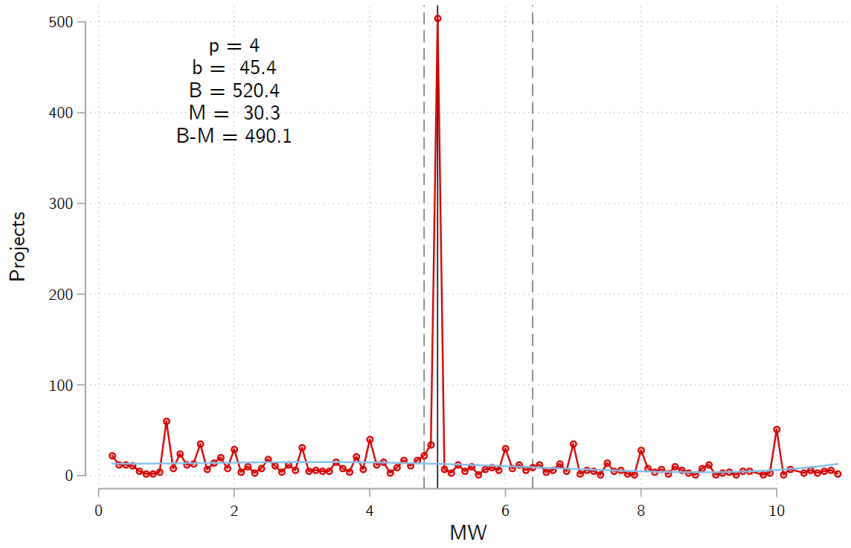


FIGURE 7. MAIN BUNCHING ESTIMATION

Notes: p represents the polynomial, b is the ratio of excess mass to counterfactual mass, B is the excess mass, M is the missing mass.

These estimates are lower-bounds for the reason explained in section V.B and because there could be more entry driven by the FiT below q- that the estimator is unable to capture. Visually, it is also intuitive that the response is largely on the extensive margin, since if it were driven by strategic downsizing, we would expect to see a hole above 5 MW.

Lastly, one may question whether there is "cheating" where a 10 MW project passes by as two separate 5 MW projects. I can test this by using geolocation data and measuring the distance between all 5 MW projects. Only 20 of 511 projects (3.9%) have identical locations,

[23] The reason it is "at least" 43 times is because the excess mass is only calculated around the bunching zone. There could be additional solar projects that are attributable to the FiT below the bunching area (i.e., between 0-4.9 MW) but these are not captured by the bunching estimation since causal identification requires restricting analysis to a local area.

raising suspicions that they might be cheating. I find that these projects are registered under legally separate entities, but it still raises questions about plausible tacit collusion. Nevertheless, since this is such a small share of the overall sample, the main results still hold.

D. Dynamic Bunching

Finally, I estimate the amount of bunching over three different time periods: (i) phase 1 i.e., April 2010 to July 2012, (ii) phase 2 i.e., August 2012 to December 2015, and (iii) phase 3 i.e., January 2016 to December 2019. The extent to which the FiT provides a subsidy varies across phase 1 and 2. Notably in phase 1, the FiT does not provide a subsidy (Figure 2). Phase 3 is when the pre-accreditation process was removed and since generators had no guarantee they would receive a favourable fixed tariff, it was tantamount to practically removing the policy.

The dynamic bunching estimates presented in Figure 8 show that in phase 2 there are at least 41 times more projects relative to a no-FiT counterfactual, while in phase 1, there are 27 times more projects (see Appendix E for bunching graphs by phase). In both cases, the extensive margin response is driving the vast majority of bunching.[24] It is unsurprising that there is a larger response when the FiT is a subsidy, but interestingly, there is significant bunching even when the FiT is not a subsidy, highlighting how firms value the pure price volatility elimination effect of the policy. This is interesting because it demonstrates how a revenue neutral policy (i.e. a FiT where the tariff equals the expected wholesale price) can still confer value to generators. Finally, in phase 3 there is no bunching, as would be expected since the scheme is highly diluted/has not guarantees for generators (Item 3, Appendix E).

[24] I choose to estimate in groups of years rather than individual years to avoid sample size reductions and loss of statistical power.

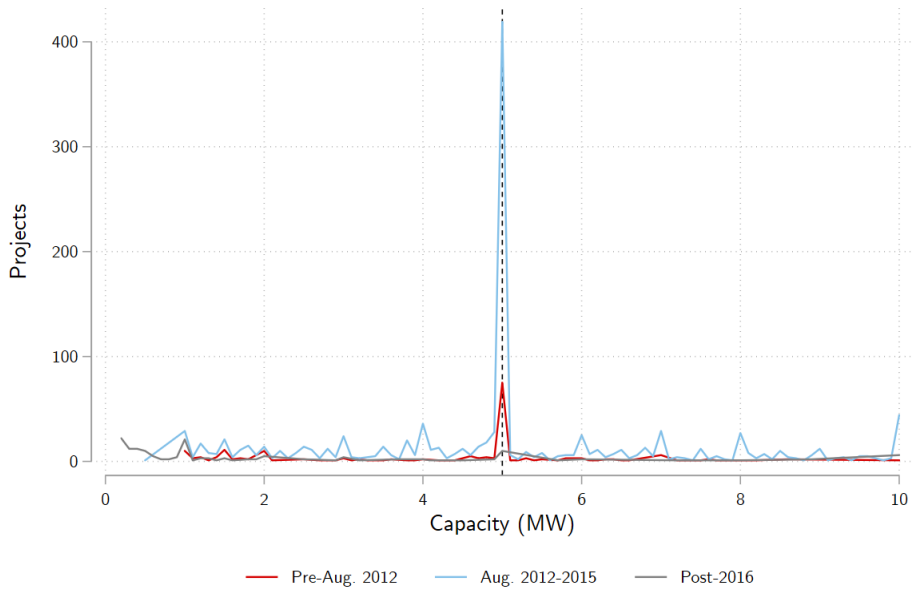


FIGURE 8. BUNCHING OVER DIFFERENT PERIODS OF TIME

Note, one could claim firms form wrong expectations about the extent to which the FiT is a subsidy. However, as long as the way firms form expectations is constant across time periods, the difference in the bunching is driven by changes in the FiT itself (i.e., the different tariff/subsidy levels). More generally, one could argue that other variables apart from the export tariff changed, and that these factors may have affected the relative amount of bunching. However, this is only a concern if we think variables are changing *differentially* at the FiT eligibility threshold in both cases. For example, solar panel costs decline between phase 1 and phase 2 but these cost reductions are exogenous to the eligibility threshold. Therefore, estimates of the excess mass should not be affected by solar panel costs.

VI. Dose-Response Estimation

The presence of bunching demonstrates that firms valued the FiT. I now proceed with a dose response estimation to examine the marginal effect of an increase in the extent to which the FiT is a subsidy on entry, as well as the marginal effect of an increase in electricity price volatility. The idea is to disentangle the relative contribution of the subsidy vs. volatility effect. Recall that if market prices are more volatile, the shielding effect of the FiT has more value.

Due to solar energy's small share in the market, fluctuations in the monthly average wholesale price are taken as exogenous.[25] This allows me to use the *difference* in the export tariff and wholesale price to estimate the effect of the "export subsidy" on entry. I assume firms look at the extent to which the FiT is a subsidy in the previous three months and use this to form expectations about the extent to which it is a subsidy in the current month.[26] Similarly, they look at average monthly volatility across the last three months to form expectations about volatility in the current month. I include the generation subsidy as a sense-check that this did not have an impact. See Equation 9:

$$(9) \qquad c_t = \beta_0 + \beta_1 E_t exp_sub_t + \beta_2 E_t gen_sub_t + \beta_3 E_t volatility_t + X'B + e_t$$

where β_1 and β_2 capture the subsidy effects and β_3 measures the volatility effect, and X represents a vector of controls including year fixed effects and seasonality. A Poisson specification is used since the outcome variables reflects count data.

Year fixed effects are needed due to the concern that changes in the electricity price may be driven by general macroeconomic conditions which affect the feasibility of solar projects through channels apart from changes in the wholesale electricity price. They also control for declines in solar panel costs. Month dummies help control for seasonality. This is important because weather can separately affect both wholesale prices and solar entry. For example, winter leads to changes in wholesale electricity prices and can separately dampen market sentiments about solar since the hours of sunshine are highly diminished.

There may be additional shocks that affect wholesale electricity prices and separately (influence the feasibility solar project proposals. This could warrant the inclusion of year-month fixed effects, yet these cannot be employed as they would absorb the level at which I have variation in the independent variables of interest. However, as long as these shocks affect solar through the subsidy channel, they are not a threat to identification. Finally, I

[25] Solar generation has accounted for less than 2.5% percent of average annual electricity generation in the years considered within this analysis. In 2010, it accounted for only 0.01%, in 2011: 0.07%, 2012: 0.37%, 2013: 0.57%, 2014: 1.12%, and 2015: 2.25% (Source: Our World in Data, 2022

[26] I do not use futures prices since the future market was relatively under-developed during this period and subject to fluctuations based on idiosyncratic expectations based on the gas market. The mean square error of futures prices exceed that which is based on extrapolations using past price trends. The assumption that firms likely formed expectations using past prices is validated by an expert interview with Aurora Energy.

check if variables of interest are trending, which could lead to spurious correlation, but I find no evidence for this (see Appendix F).

	Entry $\leq$ 5 MW pre-2016			
	Poisson Specifications			
	I	II	III	IV
σ_p	0.120	0.151	0.242	0.243*
	(0.134)	(0.127)	(0.211)	(0.124)
exp_sub	0.099***	0.101***	0.081*	0.081***
	(0.033)	(0.030)	(0.049)	(0.028)
gen_sub	−0.005	−0.008	−0.003	−0.002
	(0.007)	(0.009)	(0.009)	(0.005)
seasonality	×	✓	✓	✓
year_fe	×	×	✓	✓
size_fe	×	×	×	✓
R^2	0.22	0.26	0.32	0.74
N	132	132	132	132

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 1. DOSE-RESPONSE POISSON ESTIMATION

Notes: N is number of months in which I have the count of new solar proposals

I restrict the sample to the count of new projects that enter at FiT-eligible capacities and focus on the years before the FiT scheme was highly diluted, i.e. pre-2016. This allows me to more precisely estimate how the relevant generators' incentives were impacted due to changes in FiT subsidy and volatility levels.[27]

I find that a one GBP per MWh increase in the FiT export subsidy (mean: £9.50) leads to 8% increase in the number of solar proposals, and this effect is significant at the 1% confidence level (see Specification IV, which is the preferred estimation). Similarly, I find that a unit increase the standard deviation of wholesale electricity prices (mean: 5.6) leads to a 27% increase in FiT-accredited solar project proposals. The effect is significant at the 10% confidence level. Another way of interpreting this is as follows: A 1% increase in the export subsidy induces a 0.84% increase in entry. A 1% increase in price volatility induces a 1.5%

[27] This also gives an overall sense of what happens in the market since most of the activity is concentrated at or below 5 MW.

increase in entry under the FiT. Overall, this suggests that both the level of subsidy and degree of volatility are important factors for entry.

VII. Value for Money

To close my analysis, I consider whether the FiT represented value for money. I do a very simple back-of-the-envelope style calculation that uses the (lower-bound) estimates of net solar capacity additions due to the FiT. I assume that this generation crowds out energy with an average emissions intensity of 0.25-0.4 tCO2/MWh (this range reflect the "cleanliness" of the UK grid during my time period of analysis). I estimate the benefit of that emissions reduction by multiplying it by the social cost of carbon. This benefit is weighed against the cost of subsidizing the FiT-accredited generation, which is measured in terms of the average difference between the wholesale price and the fixed tariff (see Appendix G for full details related to the calculation). I find that it takes a social cost of carbon worth £16 to 26 per tonne of CO2 to make the FiT a net gain for society. For comparison, the lower bound estimates of the social cost of carbon from the literature are £60 t/CO2 (Pindyck 2018) and prevailing carbon market prices in the UK are about £65/tCO2. This highlights how the commercial application of the FiT represented relatively good value for money.[28]

The government's objectives with the commercial FiT included not only emission reductions but also improving grid diversity, ensuring local buy-in for the energy transition (via a geographic distribution of low-carbon generation), fostering innovation, and increasing energy independence (DECC 2015a). Testing all of these aims formally is beyond the scope of this paper, however some descriptive information is provided.

In terms of creating more buy-in for the energy transition, while I do not have survey data on British attitudes before and after the FiT, I can use certain proxy variables. For example, since these projects require local council approval, a location with a FiT project is also an area where elected community representatives approved of its development. Insofar as

[28] Government documentation calculates the value-for-money across both the commercial and residential FiT. This is misleading because while households got as much as £500/MWh for the solar they generated for self-consumption (see Figure A.3. in Appendix H for a summary of self-generation tariffs), commercial generators got £40-55/MWh. By clubbing these two very different policies, the UK government got a value-for-money figure worth £400/tCO2. This led to the eventual scrappage of both FiTs, even though, as this paper shows, the commercial FiT had relatively good value for money.

project approval is an indicator of local buy-in, we can see that the FiT achieved buy-in across a large geographic area (Figure A.2 in Appendix H).

In terms of innovation, Gerarden (2022) uses methods in industrial organisation and structural estimation to find that the boost in demand due to FiTs results in more production, which leads to learning-by-doing effects. This in turn results in higher solar panel efficiencies, and consequently, even greater diffusion beyond the first-order effect of the policy.

Finally, there is a question of *why* solar became the main beneficiary of the policy and if it crowded-out other low-carbon technologies. Recall that the FiT was available to other low-carbon technologies, including onshore wind generation. However, it is possible that due to the modularity of solar, it was easier for it to meet the 5 MW eligibility threshold relative to wind power. It is unclear what the welfare implications of this are because on one hand, having diverse generation technologies helps in system stability and managing intermittency (from this perspective, solar is beneficial since the UK already had wind), but on the other hand, capacity factors for onshore wind are higher than that of solar (26% vs. 11%) and as such, wind is better at pushing out dirty generation. These questions relate to optimal policy design and are worth investigating in future work.

VIII. Conclusion

This paper asks how breakthrough technologies can be brought to market to meet societal goals, focusing on the case of clean energy. This question is motivated by the hypothesis that due to credit market imperfections and positive externalities, investment in clean energy is sub-optimally low.

Using a bunching estimator, I find that the UK's renewable energy feed-in-tariff (FiT) was effective in incentivising large amounts of entry and investment by solar generators, with minimal amounts of strategic downsizing. This results in significant low-carbon capacity additions. The very large extensive margin response shows how this policy helped bring utility-scale solar energy to market, especially since prior to the FiT such projects did not exist in the UK power grid. Value for money calculations show it only takes a social cost of carbon worth 16-26 GBP/tCO2 to make the policy a net gain.

Dynamic bunching shows how even when the FiT does not provide a subsidy (because the fixed tariff ≤ wholesale price), there is still significant bunching because firms value the price volatility elimination component of the policy. As the FiT provides a subsidy, bunching increases from 27 times to 40 times, relative to a no-FiT counterfactual.

While this paper conducts an empirical case study on solar energy, the broader question on the role of risk-reduction in bringing breakthrough technologies to market is likely to have relevance to other technologies such as second-generation low carbon technologies (e.g. green fuels, long duration storage, zero-carbon steel, etc.) and healthcare innovation. Technologies in these domains also generative positive externalities and face credit market imperfections.

In terms of limitations, this work concerns itself with case of policy for nascent breakthrough technologies, which occupy a small share of the market and can be modelled a price-takers. My conclusions do not have external validity when applied to technologies with higher market shares. This is because the distortionary effects of price volatility dampening on overall market outcomes can no longer be approximated away (this includes the impact on investment portfolios, incentives to invest in energy storage, and market clearing). The results of this paper, therefore, should be contextualised in the case of early-stage/breakthrough technologies. To explore broader questions around the optimal deployment of the FiT, beyond the case of early-stage technologies, a new model with endogenous prices and a market for credit will be needed. This is a promising avenue for future work.

IX. References

Aguerrevere, F.L., 2003. Equilibrium investment strategies and output price behavior: A real-options approach. The Review of Financial Studies, 16(4), pp.1239-1272.

Al Mamun, M., Sohag, K., Shahbaz, M. and Hammoudeh, S., 2018. Financial markets, innovations and cleaner energy production in OECD countries. Energy Economics, 72, pp.236-254.

Aldy, J.E., Gerarden, T.D. and Sweeney, R.L., 2018. Investment versus output subsidies: Implications of alternative incentives for wind energy (No. w24378). National Bureau of

Economic Research.

Allen, E.J., Dechow, P.M., Pope, D.G. and Wu, G., 2017. Reference-dependent preferences: Evidence from marathon runners. Management Science, 63(6), pp.1657-1672.

Bachas, P.J. and Soto, M., 2018. Not(ch) your average tax system: corporate taxation under weak enforcement. World Bank Policy Research Working Paper, (8524).

Baker, E., M. Fowlie, D. Lemoine, and S. S. Reynolds 2013. The Economics of Solar Electricity. Annual Review of Resource Economics 5(1), 387–426.

Best, M.C. and Kleven, H.J., 2018. Housing market responses to transaction taxes: Evidence from notches and stimulus in the UK. The Review of Economic Studies, 85(1), pp.157-193.

Bloom, N., 2007. Uncertainty and the Dynamics of R&D. American Economic Review, 97(2), pp.250-255.

Bloom, N., Bond, S. and Van Reenen, J., 2007. Uncertainty and investment dynamics. The review of economic studies, 74(2), pp.391-415.

Boomsma, T.K. and Linnerud, K., 2015. Market and policy risk under different renewable electricity support schemes. Energy, 89, pp.435-448.

Boomsma, Trine Krogh, Nigel Meade, and Stein-Erik Fleten. 2012. Renewable energy investments under different support schemes: A real options approach. European Journal of Operational Research 220, no. 1: 225-237.

Borenstein, S., 2012. The private and public economics of renewable electricity generation. *Journal of Economic Perspectives*, *26*(1), pp.67-92.

Brunnschweiler, C.N., 2010. Finance for renewable energy: an empirical analysis of developing and transition economies. Environment and development economics, 15(3), pp.241-274.

Byoun, S., Kim, J. and Yoo, S.S., 2013. Risk management with leverage: Evidence from project finance. *Journal of Financial and quantitative analysis*, *48*(2), pp.549-577.

Calel, R., 2020. Adopt or innovate: Understanding technological responses to cap-and-trade. American Economic Journal: Economic Policy, 12(3), pp.170-201.

Chetty, R., 2012. Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply. Econometrica, 80(3), pp.969-1018.

Chetty, R., Friedman, J.N. and Saez, E., 2013. Using Differences in Knowledge across

Neighborhoods to Uncover the Impacts of the EITC on Earnings. American Economic Review, 103(7), pp.2683-2721.

Chetty, R., Friedman, J.N., Olsen, T. and Pistaferri, L., 2011. Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: Evidence from Danish tax records. The Quarterly Journal of Economics, 126(2), pp.749-804.

Clifford, S. and Mavrokonstantis, P., 2021. Tax enforcement using a hybrid between self- and third-party reporting. Journal of Public Economics, 203, p.104519.

Cumming, D.J., Leboeuf, G. and Schwienbacher, A., 2017. Crowdfunding cleantech. Energy Economics, 65, pp.292-303.

De Groote, O. and F. Verboven (2019). Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems. American Economic Review 109(6), 2137–2172.

DECC 2015a. Performance and Impact of Feed-in-Tariff Scheme: Review of Evidence. Report.

DECC 2015b. Consultation on a Review of the Feed-in Tariffs Scheme. Public Consultation.

Dijkgraaf, E., van Dorp, T.P. and Maasland, E., 2018. On the effectiveness of feed-in tariffs in the development of solar photovoltaics. The Energy Journal, 39(1).

Dixit, A.K. and Pindyck, R.S., 1994. Investment under Uncertainty. Princeton University Press.

Gaddy, B.E., Sivaram, V., Jones, T.B. and Wayman, L., 2017. Venture capital and cleantech: The wrong model for energy innovation. Energy Policy, 102, pp.385-395.

Germeshausen, R. 2018. Effects of attribute-based regulation on technology adoption–the case of feed-in tariffs for solar photovoltaic. ZEW-Centre for European Economic Research Discussion Paper, (18-057).

Grenadier, S.R., 2002. Option exercise games: An application to the equilibrium investment strategies of firms. The Review of Financial Studies, 15(3), pp.691-721.

Grover, David. 2013. The British Feed-in-Tariff for small renewable energy systems: Can it be made fairer? Policy Paper. Grantham Research Institute on Climate Change and the Environment.

Groobey, C., Pierce, J., Faber, M. and Broome, G., 2010. Project finance primer for

renewable energy and clean tech projects. Wilson Sonsini Goodrich & Rosati.

Hassler, John A. A., 1996. Variations in risk and fluctuations in demand: A theoretical model, Journal of Economic Dynamics and Control, Elsevier, vol. 20(6-7), pages 1115-1143.

Hausman, C. and Rapson, D.S., 2018. Regression discontinuity in time: Considerations for empirical applications. Annual Review of Resource Economics, 10, pp.533-552.

Howell, S.T., 2017. Financing innovation: Evidence from R&D grants. American Economic Review, 107(4), pp.1136-64.

Hughes, J. E. and M. Podolefsky (2015). Getting Green with Solar Subsidies: Evidence from the California Solar Initiative. Journal of the Association of Environmental and Resource Economists 2(2), 235–275.

IEA 2021. World Energy Outlook 2021.

Jenner, S., Groba, F. and Indvik, J., 2013. Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries. Energy Policy, 52, pp.385-401.

Johnstone, N., Haščič, I. & Popp, D. 2010. Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts. Environmental and Resource Econonomics 45, 133–155.

Kellogg, R., 2014. The Effect of Uncertainty on Investment: Evidence from Texas Oil Drilling. American Economic Review, 104(6), pp.1698-1734.

Kleven H.J., Landais C., Søgaard J. 2016. The breadwinner notch: A bunching approach to estimating reference-dependent preferences. Working Paper.

Kleven, H.J. and Waseem, M., 2013. Using notches to uncover optimization frictions and structural elasticities: Theory and Evidence from Pakistan. The Quarterly Journal of Economics, 128(2), pp.669-723.

Kleven, H.J., 2016. Bunching. Annual Review of Economics, 8, pp.435-464.

Kőszegi, B. and Rabin, M., 2006. A model of reference-dependent preferences. The Quarterly Journal of Economics, 121(4), pp.1133-1165.

Leroutier, M. 2022. Carbon pricing and power sector decarbonization: Evidence from the UK, Journal of Environmental Economics and Management, Volume 111, 102580.

Martin, R., De Preux, L.B. and Wagner, U.J., 2014. The impact of a carbon tax on manufacturing: Evidence from microdata. Journal of Public Economics, 117, pp.1-14.

Nanda, R., Younge, K. and Fleming, L., 2015. Innovation and entrepreneurship in renewable energy. The changing frontier: Rethinking science and innovation policy, pp.199-232.

Nemet, G.F., Zipperer, V. and Kraus, M., 2018. The valley of death, the technology pork barrel, and public support for large demonstration projects. Energy Policy, 119, pp.154-167.

Ofgem. 2016. Feed-in Tariff Annual Report 2016.

Ofgem. 2019. Feed-in Tariff Annual Report 2019.

Pindyck, R.S., 2019. The Social Cost of Carbon Revisited. Journal of Environmental Economics and Management, 94, pp.140-160.

Pollinger, S. 2021. Kinks Know More: Policy Evaluation Beyond Bunching with an Application to Solar Subsidies. Mimeo.

Polzin, F., Egli, F., Steffen, B. and Schmidt, T.S., 2019. How do policies mobilize private finance for renewable energy? A systematic review with an investor perspective. Applied Energy, *236*, pp.1249-1268.

Ramstein, C., Dominioni, G., Ettehad, S., Lam, L., Quant, M., Zhang, J., Mark, L., Nierop, S., Berg, T., Leuschner, P. and Merusi, C., 2019. State and Trends of Carbon Pricing 2019. The World Bank.

Ryan, N., 2021. Holding Up Green Energy (No. w29154). National Bureau of Economic Research.

Saez, E., 2010. Do Taxpayers Bunch at Kink Points? American Economic Journal: Economic Policy, 2(3), pp.180-212.

Sallee, J.M. and Slemrod, J., 2012. Car notches: Strategic automaker responses to fuel economy policy. Journal of Public Economics, 96(11-12), pp.981-999.

Schildermans et al. 2022. Split incentives, imperfect information and energy-efficiency subsidies. Mimeo.

Sendstad, L.H. and Chronopoulos, M., 2020. Sequential investment in renewable energy technologies under policy uncertainty. Energy Policy, 137, p.111152.

Slemrod, J., 2013. Buenas notches: lines and notches in tax system design. Working Paper, University of Michigan

Smith, M.G. and Urpelainen, J., 2014. The effect of feed-in tariffs on renewable electricity generation: An instrumental variables approach. *Environmental and Resource Economics*,

57(3), pp.367-392.

Speer, B., Mendelsohn, M. and Cory, K. 2010. Insuring Solar Photovoltaics: Challenges and Possible Solutions. NREL. Technical Report.

Steckel, J.C. and Jakob, M., 2018. The role of financing cost and de-risking strategies for clean energy investment. International Economics, 155, pp.19-28.

Steffen, B., 2018. The importance of project finance for renewable energy projects. Energy Economics, 69, pp.280-294.

Steffen, B., 2020. Estimating the cost of capital for renewable energy projects. Energy Economics, 88, p.104783.

Stoel Rives. 2017. The Law of Solar: Guide to Business and Legal Issues. Fifth Edition.

Taghizadeh-Hesary, F. and Yoshino, N., 2020. Sustainable solutions for green financing and investment in renewable energy projects. Energies, 13(4), p.788.

X. Appendix

A. Solving for the Wait Value Function

The value of waiting is given by Equation A.1

(A.1) $$\max_{q} V_t^w = \beta\{E_t \mathrm{V}_{t+1}^{\mathrm{w}}, E_t \mathrm{V}_{t+1}^{\mathrm{FiT}}, E_t \mathrm{V}_{t+1}^{\mathrm{I}}\}$$

The expected value of entering with a FiT next period is:

(A.2) $$E_t \mathrm{V}_{t+1}^{\mathrm{FiT}} = \frac{\bar{p} q_{t+1}^{f*}}{1-\beta} - \mu_{\chi_i} f(q_{t+1}^{f*})$$

Note that in expectation, the choice of optimal installed capacity time across periods under a FiT is the same, that is $E_t q_{t+1}^{f*} = E_t q_{t+2}^{f*} = \cdots = E_t q_{t+T}^{f*}$. This is because the variables that affect optimal choice do not change in expectation: price does not change across time (it is always the FiT rate, $\bar{p}$) and in expectation, the cost shock is μ_{χ_i} is also the same. Therefore, the value of entering with a FiT is the same: $E_t V_{t+1}^{FiT} = E_t V_{t+2}^{FiT} = \cdots = E_t V_{t+T}^{FiT} \equiv \hat{V}^{FiT}$.

(A.3) $$E_t V_{t+1}^{FiT} = E_t V_{t+2}^{FiT} = \cdots = E_t V_{t+T}^{FiT} \equiv \hat{V}^{FiT}$$

This implies that it is always better to enter with a FiT today rather than tomorrow in expectation, since $\hat{V}^{FiT} > \beta \hat{V}^{FiT}$.

A similar logic applies to the value of investing without any policy support.

(A.4) $$E_t V_{t+1}^{I} = E_t V_{t+2}^{I} = \cdots = E_t V_{t+T}^{I} \equiv \hat{V}^{I}$$

This is because in expectation, the price equals μ_p in every time period, and the cost shock is μ_{χ_i}. These variables affect the optimal choice of installed capacity, which in expectation is also then equal across time periods. A.4 implies that in expectation, it is better to invest today than tomorrow: $\hat{V}^{I} > \beta \hat{V}^{I}$. It is important to note that this is in *expectation*. Once the cost

shock of the current time period is realized, it may be so unfavourable that waiting till the next period is optimal.

Substituting A.4. and A.3. into A.1. and recursively solving the value of waiting yields:

(A.5) $$\max_{q} V_t^w = \beta \max\{\widehat{V}^{FiT}, \widehat{V}^I\}$$

Note as $T \to \infty$, $\beta^T \to 0$ and $\beta^T V_{t+T}^w \to 0$. Without the FiT, the value of waiting will be the discounted expected value of investing, as shown in Equation A.6.

(A.6) $$V_t^w = \beta \widehat{V}^I$$

B. Earlier Entry with a FiT

If there is no FiT, the maximisation problem is $max\{V_t^w, V_t^I\}$. Substituting for the value of waiting in A.6, we get, $max\{\beta\widehat{V}^I, V_t^I\}$. As σ_p increases, investment costs rise, and V_t^I decreases, as does $\beta\widehat{V}^I$. A firm invests today if $V_t^I > \beta\widehat{V}^I$, that is, the profit, given the realised price and realised cost shock, is greater than the discounted profit with the average price and average cost shock. A higher price volatility increases the chance of extremes, either a very favourable high price, or a very poor low price (note: wholesale electricity prices are allowed to become negative, so there is no asymmetric impact of price volatility increases). We are unable to comment on whether higher volatility necessarily delays entry – it just creates more unpredictability.

If there is a FiT, then given a sufficiently attractive tariff rate (which is at least equal to the expected average price of electricity), there is likely to be more entry today relative to a scenario where there is no FiT. V_t^{FiT} does not change in the volatility of the market price of electricity. All else equal, if σ_p increases, the value of V_t^{FiT}rises relative to V_t^I (which decreases in σ_p) and possibly also V_t^W (if the maximum is $\widehat{V}^I$ as per A.5). Much still depends on the FiT rate. Entry with a FiT happens today if the profit given the FiT rate and the realised cost shock (V_t^{FiT}) is greater than the maximum of: (i) the discounted profit given the average electricity price and average cost shock ($\beta\widehat{V}^I$) and (ii) the discounted profit given the FiT rate and average cost shock ($\beta\widehat{V}^{FiT}$). Assume the FiT rate is equal to the average electricity price

and the cost shock is equal to the average, then $V_t^{FiT} > \beta \hat{V}^I$ and $V_t^{FiT} > \beta \hat{V}^{FiT}$, and as such, entry today with FiT strictly dominates and gets more attractive as σ_p increases.

In other words, a firm invests today if $V_t^I > V_t^W$ or $V_t^{FiT} > V_t^W$. As σ_p increases, V_t^{FiT} remains unchanged, while V_t^I falls. Between the two scenarios (with FiT and no FiT), there are more conditions to facilitate entry in the "with FiT" case. The intuition is that when price volatility is high, the value of investing today with no support falls, while the value of investing with a FiT does not, and this means that there is a higher chance of entry in a world with FiTs.

C. Event Study Regression

I consider observations preceding October 2015 as "treated" (i.e., in a world with an effective FiT) and those after the date as "untreated" (i.e., in a world where the policy was diluted significantly). Using a Poisson specification which is well-suited to count data, I examine how the number of new solar project proposals changes after pre-accreditation was formally removed. Equation A.7. describes the estimation where y_t is the number of new solar projects, β_j captures the effect of the change in the FiT in the months after the shock, and the third term controls for seasonality.

(A.7.) $$y_t = \alpha_t + \sum_{j=1}^{T} \beta_j \cdot \mathbb{1}\{t \geq t_{start}\} + \sum_{i=1}^{11} \gamma_i \cdot m_i + \varepsilon_t$$

As the event study plot and regression table shows, there is a highly statistically significant and sizable decline in entry rates. A month after the policy change, there is a 78% drop in new projects, which becomes a 95% drop 7 months after (albeit with higher errors around the estimate), after controlling for seasonality.

The event study plot also suggests that there were anticipation effects prior to the removal of the pre-accreditation scheme, as indicated by the increased entry rates from June 2015 onwards.[29]

[29] On 22 July 2015, it was announced that a consultation would be held on whether pre-accreditation should be removed. Even though almost all generators opposed the removal of the pre-accreditation process, it was nevertheless announced in September 2015, that it would be removed. The policy took effect on October 2015.

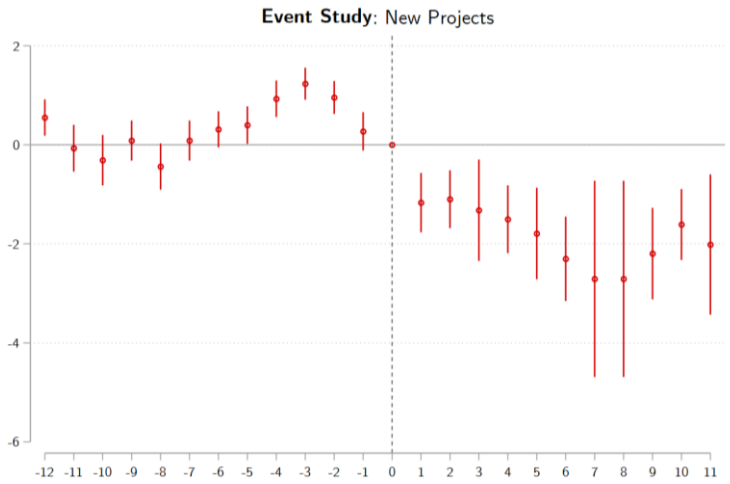


FIGURE C.1. EVENT STUDY PLOT OF MONTHLY DECLINE IN NEW SOLAR PROJECTS

One cannot control for all changes across time that may have affected entry in such an empirical design. Therefore, the results are presented in the spirit of descriptive evidence.

TALBE C.1. EVENT STUDY POISSON REGRESSION

Poisson Specification	**(1)**
	Number of Projects
	b/se
Month before event at t	
t-1	.2017396
	.1567967
t-2	-.2631489
	.179368
t-3	-.6584616***
	.2392055
t-4	-.2631489
	.179368
t-5	-.5714502***
	.1805493
t-6	8.09e-17
	.153393
t-7	-.3263278*
	.1830405
t-8	.0497234
	.163371
t-9	.7125653***
	.1394884
t-10	.8852249***
	.128915
t-11	.2638714*
	.1543143
t-12	-.0774317

	.1694516
Oct-15	0
	.
t+1	-1.515912***
	.2884324
t+2	-1.446919***
	.280056
t+3	-1.670063***
	.5116295
t+4	-1.957745***
	.4224114
t+5	-2.140066***
	.460179
t+6	-2.650892***
	.4224114
t+7	-3.056341***
	1.005857
t+8	-3.056341***
	1.005857
t+9	-2.545531***
	.460179
t+10	-1.957745***
	.3505365
t+11	-2.36321***
	.7153773
t+12	3.056357***
	.1084652
R-squared	.4465238
N	66

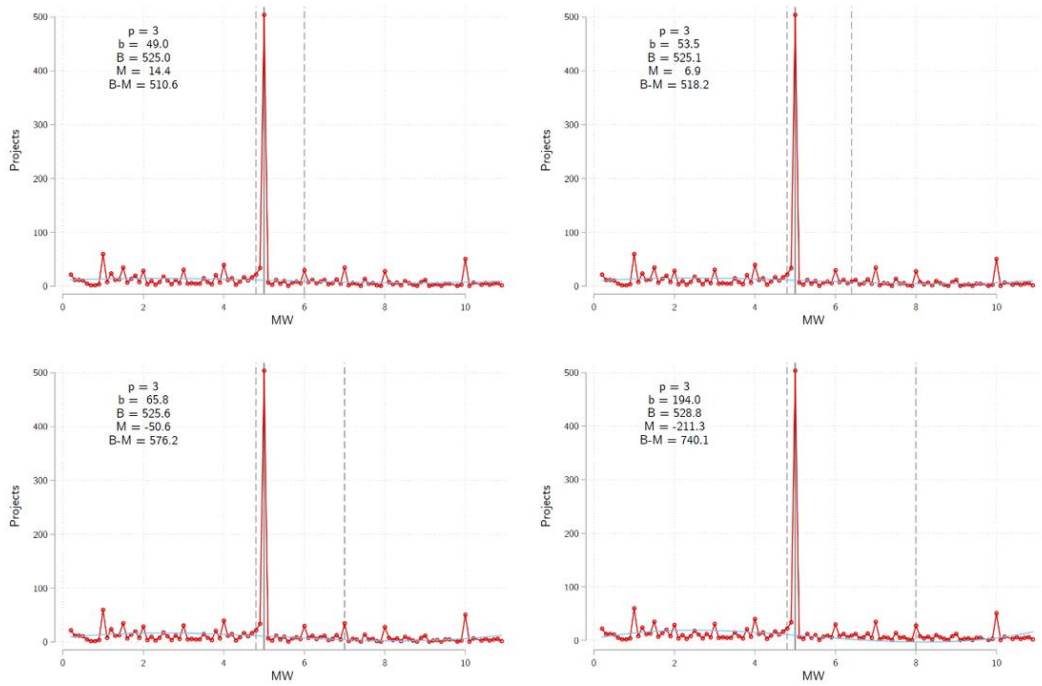
*Note: * p<0.1, ** p<0.05, *** p<0.01*

Coefficients have to be interpreted as per the standard procedure of Poisson specifications.

D. Robustness Tests for Bunching

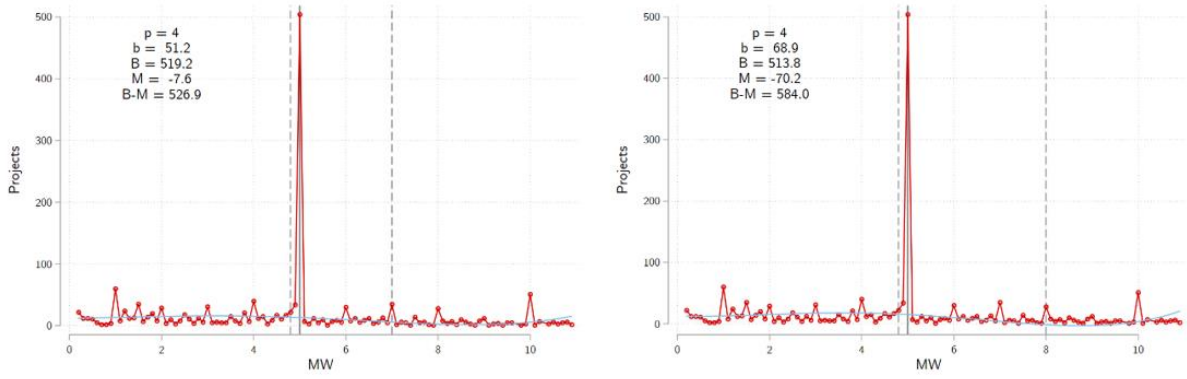
Robustness Test 1

Using a third order polynomial specification, with a lower bound at 4.9 MW and upper bounds that range from 6-8MW, I see that the amount of strategic downsizing accounts for 1-3% of the response when the upper bound is 6-6.5MW. Once the upper bound is assumed to be 7 or 8 MW, the amount of strategic downsizing takes on negative values because the observed data is higher than what the counterfactual distribution would predict, and this is the opposite of what one would expect if we believed 7-8 MW projects were downsizing to take advantage of the FiT.



Robustness Test 2

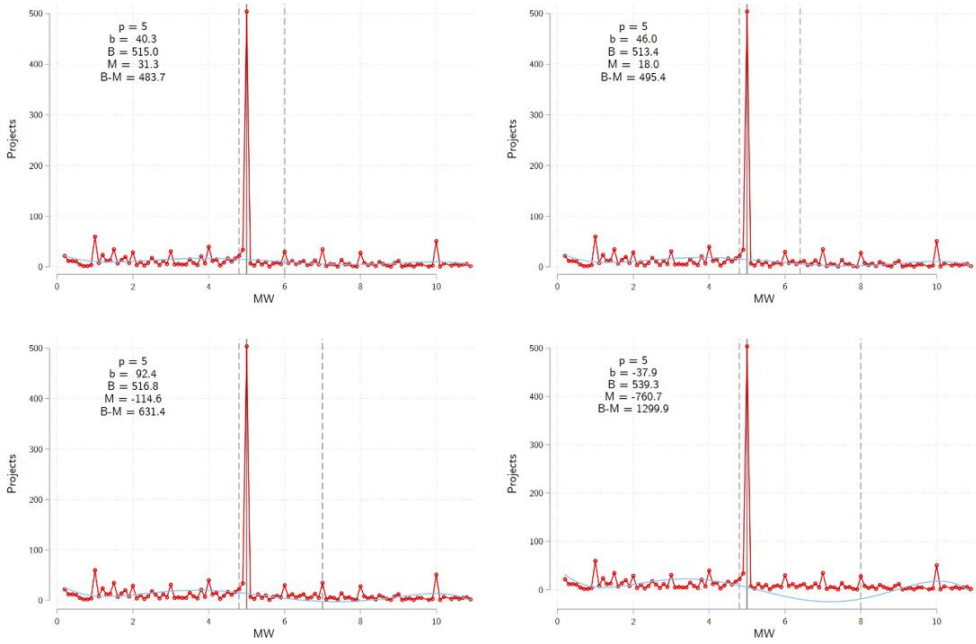
Using a fourth order polynomial specification with a lower bound at 4.9 MW and upper bounds at 7 or 8 MW, the amount of strategic downsizing takes on negative values again.



Robustness Test 3

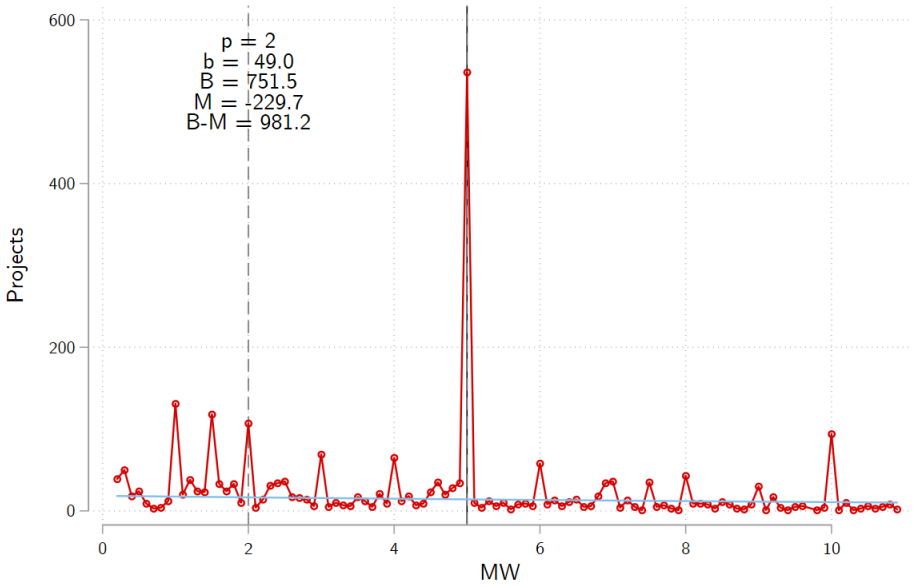
Using a fifth order polynomial specification with a lower bound at 4.9 MW and upper bounds that range from 6-8MW, I see that the amount of strategic downsizing accounts for 3-6% of the response when the upper bound is 6-6.5 MW. Once the upper bound is assumed

to be 7 or 8 MW, the amount of strategic downsizing takes on negative values, indicating that there is no strategic downsizing at these capacities.



Robustness Test 4

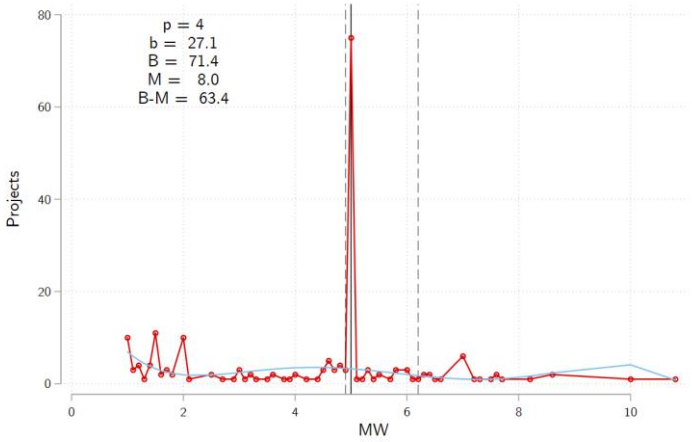
Upsizing is unlikely to be a concern since there is no visible hole towards the left of the notch. However, this is tested more formally via a bunching estimator that calculates bunching from the left (see below). The missing mass is negative which means that there are *fewer* projects towards the left of the notch in a no-FiT world relative to the with-FiT reality. This highlights that there is no upsizing and is, in fact, suggestive that the FiT created new entry at lower capacities. This is in line with the idea that the UK FiT's effect is largely about "creating the market" by incentivising large amounts of entry and new capacity. This is also aligned with descriptive evidence that finds that there were no commercial solar projects prior to the introduction of the FiT in 2010.



E. Dynamic Bunching Close-Up

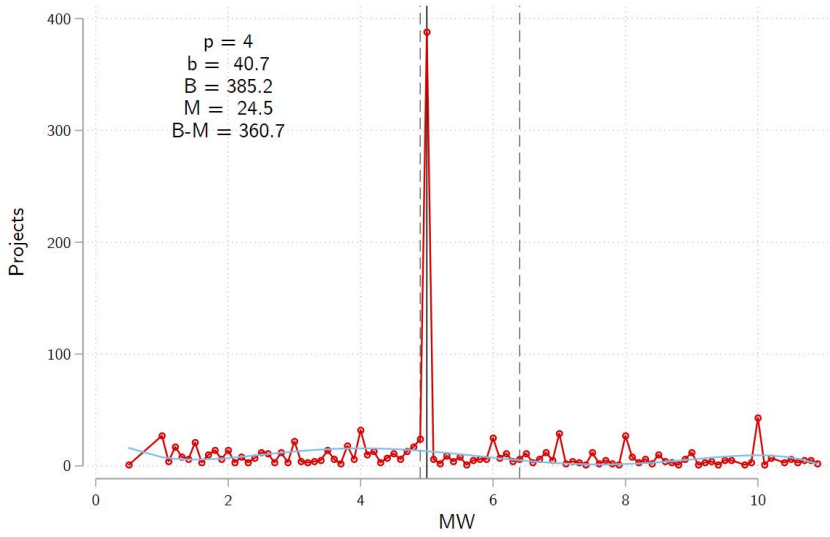
The amount of bunching in phase 1 is smaller than that in phase 2.

Item 1



PHASE 1: BUNCHING FROM APRIL 2010- JULY 2012

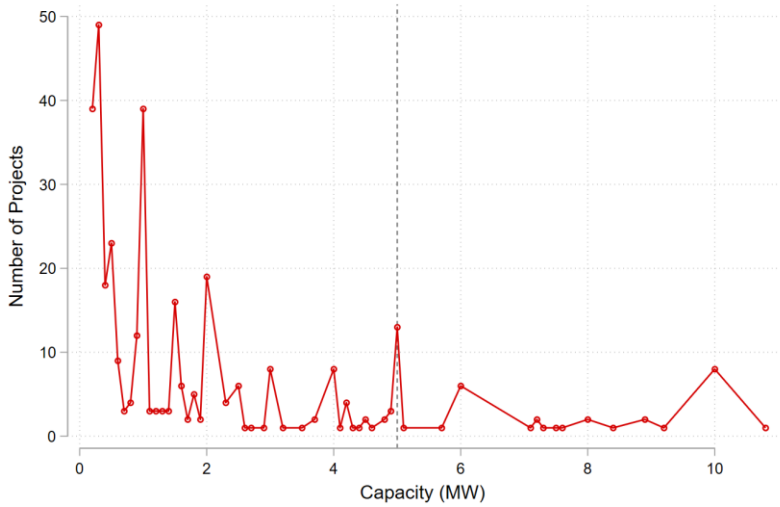
Item 2



PHASE 2: BUNCHING FROM AUGUST 2012 - DECEMBER 2015

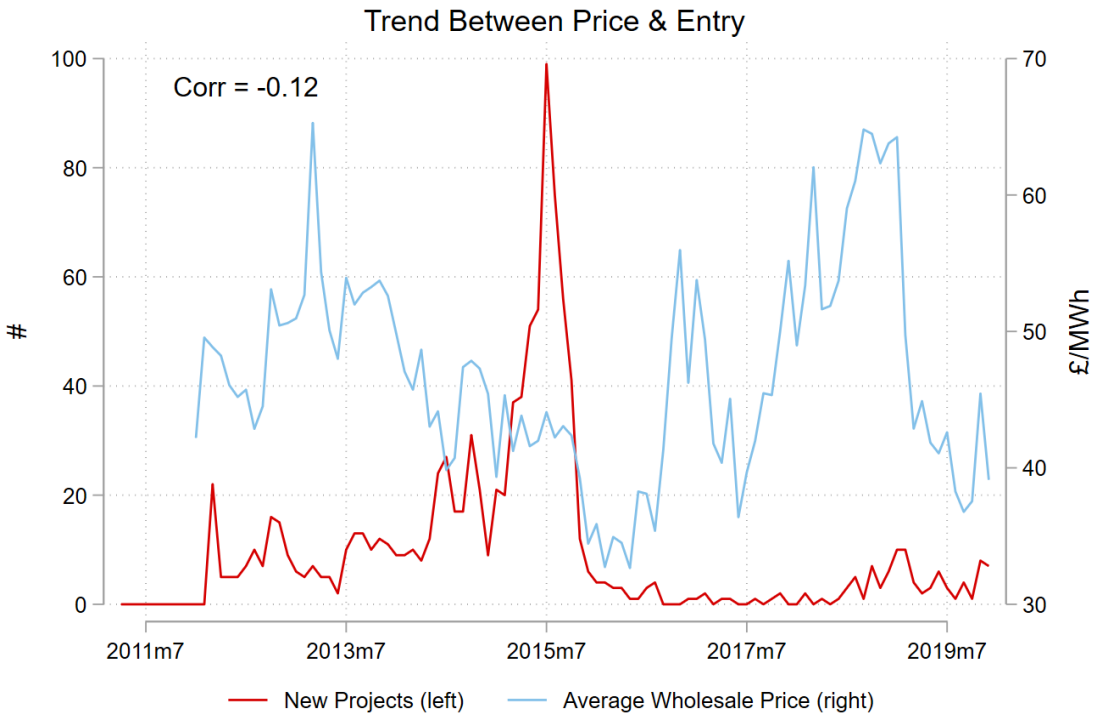
Item 3

There is no significant bunching at 5 MW anymore after Jan 2016.



PHASE 3: POST 2016 BUNCHING

F. Poisson Regression Test



G. Value for Money Calculations

Table 1: Assuming Dirty Grid

	Variables	Values	Comments
1	Net Capacity Additions due to FiT (MW)	2,270	Obtained from bunching estimates
2	Solar Load Factor	0.11	Annual average
3	Days in a Year	365	
4	Hours in a day	24	
5	Annual Solar Generation due to FiT (MWh)	2,187,372	Capacity*Days*Hours*Load Factor (lines 1-4)
6	Emissions intensity of energy displaced by solar (tCO2/MWh)	0.40	Assuming "dirty" UK grid
7	Emissions displaced by FiT Solar (tCO2/year)	874,949	Generation*Emissions Intensity (line 5* line 6)
8	Cost of Carbon (£)	65.0	Carbon Price in EU ETS (April 2022)
9	Annual value of emissions displaced by solar (£)	56,871,672	Generation*Social Cost of Carbon (line 5*line 8)
10	Net subsidy given to FiT accredited solar (£/MWh)	6.5	Export tariff - wholesale electricity price (average value)
11	Annual cost of FiT solar subsidy (£)	14,217,918	Generation*Subsidy (line 5*line 10)
12	Annual emissions benefit less cost of FiT (£)	42,653,754	(Line 9 - line 11)
13	Minimum carbon price at which benefit greater than or equal to cost	16	(Line 11 / line 7)

Table 2: Assuming Clean Grid

	Variables	Values	Comments
1	Net Capacity Additions due to FiT (MW)	2,270	Obtained from bunching estimates
2	Solar Load Factor	0.11	Annual average
3	Days in a Year	365	
4	Hours in a day	24	
5	Annual Solar Generation due to FiT (MWh)	2,187,372	Capacity*Days*Hours*Load Factor (lines 1-4)
6	Emissions intensity of energy displaced by solar (tCO2/MWh)	0.25	Assuming "cleaner" UK grid
7	Emissions displaced by FiT Solar (tCO2/year)	546,843	Generation*Emissions Intensity (line 5* line 6)
8	Cost of Carbon (£)	65.0	Carbon Price in EU ETS (April 2022)
9	Annual value of emissions displaced by solar (£)	142,179,180	Generation*Social Cost of Carbon (line 5*line 8)
10	Net subsidy given to FiT accredited solar (£/MWh)	6.5	Export tariff - wholesale electricity price (average value)
11	Annual cost of FiT solar subsidy (£)	14,217,918	Generation*Subsidy (line 5*line 10)
12	Annual emissions benefit less cost of FiT (£)	127,961,262	(Line 9 - line 11)
13	Minimum carbon price at which benefit greater than or equal to cost	26	(Line 11 / line 7)

H. Figures

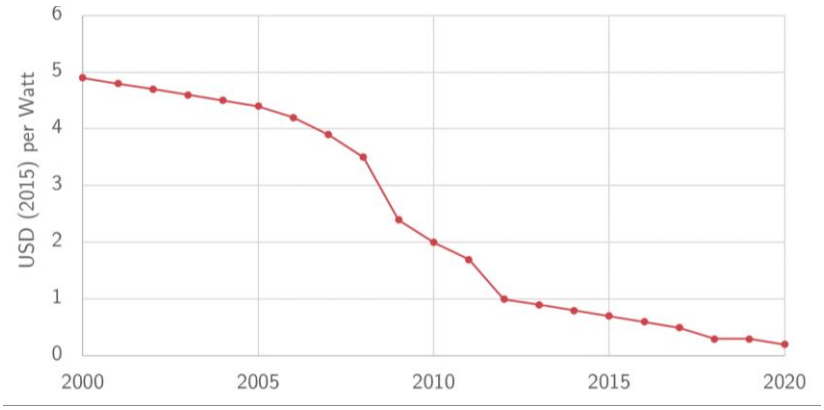


FIGURE A.1. SOLAR PANEL COSTS. SOURCE: BNEF AND NREL.

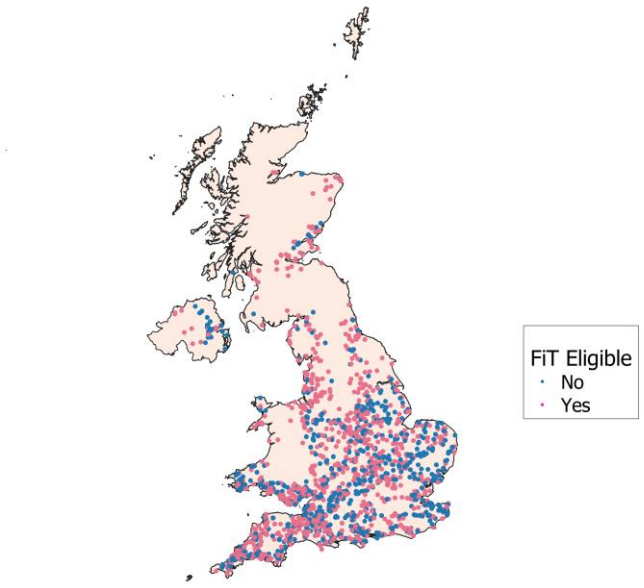


FIGURE A.2. SOLAR PROJECTS BY SIZE IN THE UK

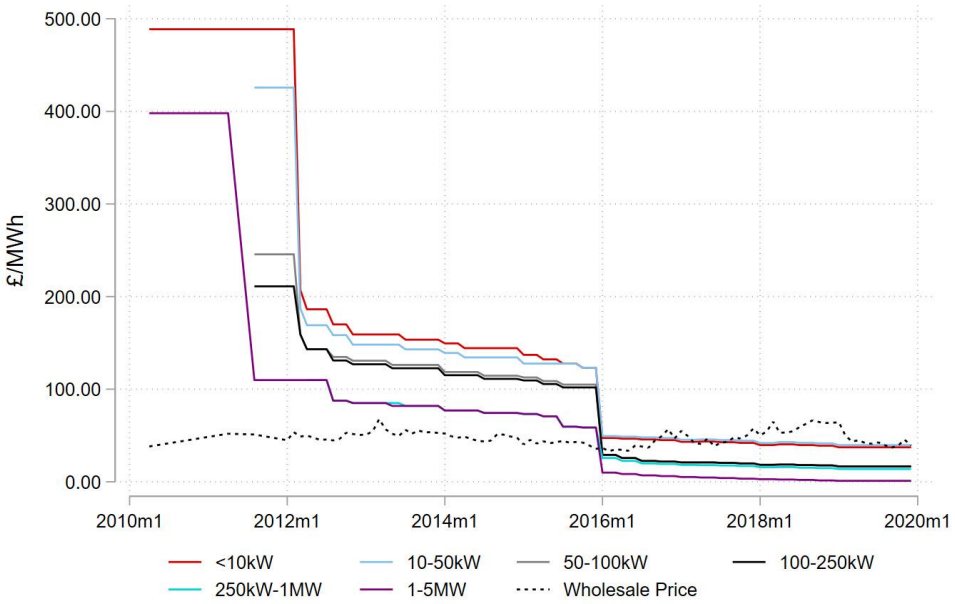


FIGURE A.3. GENERATION TARIFFS FOR RESIDENTIAL AND SMALL-SCALE SOLAR FOR SELF CONSUMPTION