Bringing Breakthrough Technologies to Market: Evidence from Renewable Energy Projects

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Due to uncertainties, irreversible investments, and positive externalities, many socially-beneficial breakthrough technologies are under-provided in equilibrium. I examine how to bring these technologies to market in a timely manner, focusing specifically on the case of clean energy which is essential to address climate change. I causally estimate the effect of the United Kingdom's feed-in-tariff (FiT), which provides low-carbon power generators a fixed tariff for electricity sold to the grid. Exploiting the presence of bunching at the policy's eligibility threshold, I find that there are at least 43 times more commercial solar projects relative to a no-FiT counterfactual. The majority of this response is on the extensive margin: only 6% of generators strategically downsize while the remaining 94% are new entrants, resulting in an additional 2.3 GW of solar capacity (one-fifth of the UK's total solar capacity). I undertake some simple value-for-money calculations which reveal that even for relatively low values of the social cost of carbon (i.e., £16-26/tCO2), the commercial application of the FiT represents a net gain. Dynamic bunching, dose-response estimation and model calibration are used to size and separate the volatility effect of the FiT from its subsidy effect.

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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 and extreme weather events illustrate the value of risky breakthrough technologies such as vaccines and climate-resilient infrastructure. These technologies can save lives and help avoid significant economic damage. However, they remain under-provided due to the inability of investors to fully hedge against risk due to uncertainties, irreversible investments, and positive externalities (Dixit and Pindyck 1994; Jaffe, Newell, Stavins 2005). Left unaddressed, these issues slow down the scale and speed of deployment of important technologies.

In this paper, I examine how to bring socially-beneficial breakthrough technologies to market in a timely manner. I focus on the case of clean energy which is essential to address climate change and achieve net-zero emissions by 2050.

I investigate the extent to which the United Kingdom's feed-in-tariff (FiT), which provides low-carbon power generators a fixed tariff for their output, helped diffuse solar energy. Although the scheme was available to several different types of low-carbon technologies, I limit my attention to its impact on solar energy for grid export.[1,2] The fixed tariff that generators receive is called the "export tariff" since the electricity produced is exported to the power grid. Generators must have a nameplate capacity (i.e. size) that is less than or equal to 5 MW to be eligible.

[1] 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.

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

Understanding the impact of this policy is important since the UK has a target to fully decarbonize its power sector by 2035. Moreover, the issue of bringing breakthrough technologies to market applies to second-generation decarbonisation technologies such as batteries, long-duration storage, and green ammonia which will be crucial for achieving net-zero emissions, as well as, global health, climate change adaptation and other societal problems that require innovation.

To fix ideas, I develop a simple theoretical model in which the cost of capital increases in the perceived riskiness of the nascent technology.[3] Early-stage low-carbon firms are price-takers given their very small share in the power market. In each period, firms choose how much to invest and whether to wait or enter today, with or without FiT support. Investments are irreversible.[4]

The model predicts that there is more timely entry with a FiT since it reduces revenue risk. The value of entering with a FiT increases in the volatility of electricity prices and the export tariff while it decreases with the expected wholesale electricity price. The policy has both a "volatility effect", as it removes price volatility (and this reduces the cost of capital), and a "subsidy effect", since insofar as the export tariff exceeds the expected wholesale electricity price, it is a subsidy. The model predicts bunching at the FiT eligibility threshold which can be driven by: (i) inframarginal generators that would have entered in the absence of the FiT but downsize to take advantage of it and (ii) marginal generators that had no intention to enter but do so thanks to the policy.

I leverage the presence of bunching at the FiT eligibility threshold to estimate the impact of the FiT. The bunching estimator allows me to separate how much of the

[3] The majority of renewable energy investments, much like other infrastructure investments, are financed via "project-finance". In this set-up, renewable energy projects typically have no recourse to the parent corporation's funds, which allows the parent corporation to keep the project off its books. The project is evaluated solely on its own merits, such that higher project risks translate into higher required returns (Polzin et al. 2019).

[4] This is due to the site-specific nature of energy projects and the fact that costs related to due diligence and permitting are sunk.

observed bunching is due to entry versus strategic downsizing while also controlling for other factors that can drive entry such as declining solar panel costs. Provided there are no other discontinuous changes at the FiT eligibility threshold beyond the incentives created by the FiT itself, these estimates are causal. The bunching estimation shows that relative to a no-FiT counterfactual, there are at least 43 times more commercial solar projects thanks to the FiT. Out of this, only 6% of projects have strategically downsized. The remaining 94% are new entrants due to the policy, resulting in a net increase of 2.3 GW of capacity. This is roughly equal to one-fifth of the UK's current solar capacity.

I further utilize variation in the expected subsidy provided by the FiT over time to do dynamic bunching to determine how much entry is driven by the subsidy effect versus the volatility effect. In phase 1 (April 2010 to July 2012), when the export tariff is just equal or below the wholesale price in expectation (i.e., no subsidy), there are at least 27 times more solar projects relative to a no-FiT counterfactual. In phase 2 (August 2012 to August 2016), when the FiT is a net subsidy in expectation, there are at least 41 times more projects thanks to the policy. This shows how a higher expected subsidy leads to more entry, but interestingly also demonstrates that even when a FiT is not a subsidy in expectation, it still incentivizes entry. I argue this is likely due to reductions in revenue volatility that lower the cost of capital. In all cases, strategic downsizing is a very small share of the overall response.

The bunching strategy provides local estimates of the extent to which the FiT incentivised entry and net low-carbon capacity additions since causal identification requires limiting the analysis to a small window around the eligibility threshold. To get some "global" estimates, I do an event study and dose-response estimation. While these empirical strategies depend on stronger assumptions to produce causal estimates, they give an indicative sense overall effects across the sample.

First, I study an exogenous change to the FiT in September 2015. Driven by budgetary concerns, the government removed the pre-accreditation process, which guaranteed that new solar projects under the eligibility threshold would get a FiT upon entry.[5] I find that there is an 86% decline in the annual number of new solar project proposals in the year right after the announcement, which translates into an estimated 2.5 GW of lost capacity. Solar entry rates never recover to their pre-announcement levels.

Second, I conduct a dose-response estimation, which tests how much of the effect is driven by the elimination of price volatility versus the subsidy. I run a Poisson regression which uses a rich set of controls and leverages the fact that fluctuations in the wholesale electricity price are exogenous to solar energy which never exceeds 5% of all power generation in my sample. I find that a one GBP per MWh increase in the expected FiT subsidy leads to a 9% increase in the number of solar proposals while a unit increase the standard deviation of wholesale electricity prices leads to a 27% increase in entry under the FiT.

Taken together, these results underscore the important role of the FiT in the growth and diffusion of solar energy in the UK. Did the FiT represent value for money? Equipped with causal estimates of how much low-carbon generation can be attributed to the FiT, I undertake some simple value-for-money calculations which reveal that the commercial application of the policy represented a net gain even for relatively low values of the social cost of carbon (i.e., £16-26/tCO2). Note, I do not consider the broader welfare effects or the residential application of the policy, which was considerably more expensive (Grover 2013). I exclusively focus on risk-reduction and subsidies for utility-scale solar that is produced for the power grid. For governments with net-zero emissions targets and goals to decarbonise their power

[5] There were also changes in the FiT self-generation rate but this is less relevant to my study as I focus on commercial projects that produced electricity to export to the grid.

grids, I find FiTs can be an effective way to incentivise the necessary low-carbon generation in a timely manner.

This paper makes several contributions to the literature. First, it highlights the role of risk-reduction policies, such as feed-in-tariffs, in incentivising the diffusion of socially-beneficial breakthrough technologies. This has relevance to a variety of fields such as medicine and climate change adaptation where the confluence of uncertainty and unaccounted-for positive externalities results in sub-optimally low investment and entry. Second, the study of feed-in-tariffs, in the context of clean technologies, is a departure from the predominant focus on the role of carbon pricing. In many contexts, carbon pricing (i.e., "first-best" policy) is politically unfeasible (Klenert et al. 2018; Borenstein 2012), and it is worth understanding what other instruments can achieve.[6] Third, this paper provides causal estimates of the effects of FiTs on entry and low-carbon capacity additions.[7,8] This is important since FiTs have been deployed in over 30 countries around the world and are heavily debated in public discourses. Fourth, I make novel use of a dynamic bunching estimator in a setting outside the conventional realm of taxation, illustrating how this empirical technique can be deployed to study firm behaviour.

Finally, this paper limits its scope to the study of policies that help technologies in the early stages of the S-curve for technology diffusion. These technologies occupy a very small share of the market and can be modelled as price-takers. In my context, on average, solar generation is $< 2\%$ of the UK power market from 2010-2019, and

[6] Steckel and Jakob (2018) observe that when capital costs are high, carbon pricing alone is unlikely to be sufficient to achieve high shares of renewable energy sources in the power sector, complementary measures to decrease investors' capital costs are required.

[7] Smith and Urpelainen (2014) use an instrumental variables (IV) approach to estimate the impact of the FiT on aggregate renewable energy share. Their estimation is cross-country in nature (over 26 nations) and the proposed IV is the lagged FiT value. Consequently, the assumptions required for causal interpretation are much stronger than what is required by the bunching estimator used in this paper.

[8] Other cross-country empirical studies include: Jenner et al. (2013) and Dijkgraaf, et al. (2018) where evidence is most likely to be correlational rather than causal due to the difficulty in controlling for confounding factors in cross-country regressions.

FiT-eligible commercial solar is less than half of all solar. Therefore, the wider general equilibrium effects of volatility-reduction on overall market outcomes is less likely to be a concern in my particular context (this includes impact on investment portfolios, incentives to invest in energy storage[9], and market clearing). This is also a necessary requirement for the bunching estimation to be valid: if entry by one solar generator shifts market prices or alters the costs of capital for another, then my identifying assumption is invalid. To explore broader questions around the optimal deployment of the FiT, beyond the case of very 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.

My work connects to several strands of literature, including the (i) economics of renewable energy[10], (ii) empirical applications of bunching estimators[11], (iii) the economics of investment under uncertainty[12] - and its application to energy - ,[13] (iv) the literature on financing clean energy projects[14] and (v) empirical analyses of UK decarbonization policy.[15]

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, including the event study, Section V has the bunching estimation, Section VI reports the dose-response estimation, Section VII explores

[10] E.g. Baker et al. 2013, Hughes and Podolefsky 2015, De Groote and Verboven 2019; Gillingham and Tsvetanov 2019, Gerarden 2021, Aldy et al 2021

[11] E.g. Saez 2010, Chetty et al 2011, Kleven and Waseem 2013, Kleven 2016, Allen et al 2017, Clifford and Mavrokonstantis 2019, Mavrokonstantis 2019),

[12] E.g. Dixit and Pindyck 1994, Hassler 1996, Grenadier 2002, Aguerrevere 2003, Bloom et al. 2007, 2009

[13] E.g. Kellogg 2014, Boomsma et al 2012, Chronopoulos et al. 2016, Boomsma and Linnerud 2015)

[14] E.g. Howell 2017, Al Mamum et al. 2018, Gaddy et al. 2017, Cumming et al. 2017, Brunnschweiler 2010, Nanda et al. 2015, Nemet et al. 2018

[15] E.g. Martin et al. 2014, Calel 2020, Leroutier 2022, Pless and Srivastav forthcoming

simple model calibrations, Section VIII undertakes some value-for-money calculations and Section IX concludes.

II. Institutional Context

The UK has a target to fully decarbonize its power sector by 2035 and achieve net-zero emissions by 2050. The government has implemented a suite of different policies to help achieve these goals, among them a feed-in tariff (FiT).[16]

A. Breakthrough Technologies, Risk and Societal Benefits

Although solar panels are more commonplace today, they were regarded as expensive, uncertain and risky technologies back when the UK FiT was announced. As Fig A.3. shows, solar panel costs were substantially higher in 2010, bringing into question the financial viability of many solar projects. Both capital and insurance were limited or came at a significant premium (Speer, Mendelsohn and Cory 2010).

Investors looking at clean energy projects have to contend with long project horizons (>20 years), highly capital-intensive projects, volatile wholesale electricity prices and unpredictable output due to changing weather conditions. These factors affect the cost of capital which makes up a significant portion of overall renewable energy project costs (Steffen 2020). On the social side, clean energy is linked to several unaccounted-for positive externalities, such as a more stable climate, cleaner air, and lower risks to biodiversity,[17] which accrue through displacing polluting energy assets,[18] as well as knowledge externalities through learning-by-doing (Gerarden 2022).

[16] This includes (i) carbon pricing, (ii) quantity obligations for renewable energy, and (iii) policies such as the Feed-in-Tariff (FiT) and Contracts-for-Differences (CfD).

[17] Clean energy displaces dirty energy which reduces the risk of wide-scale environmental disasters such as oil spills, gas flares, or deforestation due to mining.

[18] In jurisdictions which have a carbon price, the price is often far below what is optimal (Ramstein et al. 2019; Pindyck 2019), and in almost all cases, externalities related to clean air and biodiversity remain unpriced.

"Project finance" is commonly used for renewable energy projects. The only collateral available to financiers is the renewable energy asset and its expected future cash flows (Steffan 2018). There is typically no recourse to the parent corporation's balance sheet or credit worthiness. Therefore, higher project risk translates into higher required returns and a higher cost of capital (Polzin et al. 2019).

Renewable energy projects are associated with several different types of risk which include potential delays in construction, electricity price volatility, costly due diligence, output uncertainty, new technology risks etc. (see Figure 3). This paper focuses on operating/revenue risk.

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)

B. Feed-in-Tariffs

The UK FiT provides a fixed price for each unit of electricity sold to the power grid by a commercial low-carbon generator with a nameplate capacity (i.e. size) that is less than or equal to 5 MW. This rate, called the "export tariff", lasts for 20 years and is assured via a pre-accreditation process that guarantees generators will receive

the rate before they enter the market. The FiT is available to solar photovoltaics, wind turbines, hydro turbines, anaerobic digestion, and micro combined heat & power (which has a different eligibility threshold). The policy is therefore technology neutral within the remit of low-carbon energy. The main beneficiary is solar energy which will be the focus of this paper (see Figure A.3). The FiT was introduced in April 2010 and phased out by April 2019.

The FiT also supports households and commercial enterprises that wish to generate low-carbon electricity for self-consumption (rather than export to the grid). Such entities are provided a separate tariff called the generation rate and supported installations tend to be much smaller. 80% of all FiT-accredited electricity is for self-consumption and the generation rate is borne entirely by electricity suppliers who pass it on to consumers via electricity bills. This accounts for the vast majority of the FiT scheme's costs (DECC 2015). However, 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 that produce power to export to the grid.

The export tariff was £39.50/MWh from April 2010 to July 2012 and £52.40/MWh after August 2012. For context, the average wholesale electricity price during this period was £45/MWh, with a high of £63 and low of £32. In an average year, 20% of FiT-accredited electricity is for export to the grid (Ofgem 2016).

The main empirical analysis in this paper takes place in a window around the 5 MW capacity threshold, which is orders of magnitude bigger than any home system (which is typically 3-4 kW). All entities in this window are commercial, utility-scale projects that generate to supply electricity to the grid, [19] confirming that the export tariff, as opposed to the generation tariff, is of relevance to my analysis.

[19] This is also confirmed in the Poisson regression in Section VI which shows that generators within this window are not reacting to the generation subsidy but are reacting to the export subsidy.

Due to the FiT, firms experience two changes: a complete reduction in the volatility of price, and a different price from the expected wholesale price of electricity. I will term the former of these effects the "volatility effect" and the latter the "subsidy effect". While FiTs are often referred to as subsidies, they are only subsidies when the export tariff is above the expected wholesale electricity price (see Figure 1).

FiT Tariff Rate	Subsidy	Risk-mitigation
$\bar{p} < \mu_p$	No	Yes
$\bar{p} = \mu_p$	No	Yes
$\bar{p} > \mu_p$	Yes	Yes

FIGURE 1. WHEN IS A FIT ALSO A SUBSIDY

Notes: $\bar{p}$ represents the export tariff and μ represents the expected (average) wholesale price of electricity.

Electricity suppliers 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. Note, however, that the export tariff is not always above the realised wholesale electricity price (Figure 2). In some periods, it is below, reflecting how FiT-accredited export generation can be cheaper than other sources of power.

The UK government states that the objectives of the FiT, beyond carbon emissions reduction, include: (i) diversification of types of generation, (ii) reduced dependence on imported fossil fuels, (iii) generating "buy-in" for the low-carbon transition by giving agents a direct stake, and (iv) facilitating technology costs reductions via learning-by-doing (DECC 2015a).

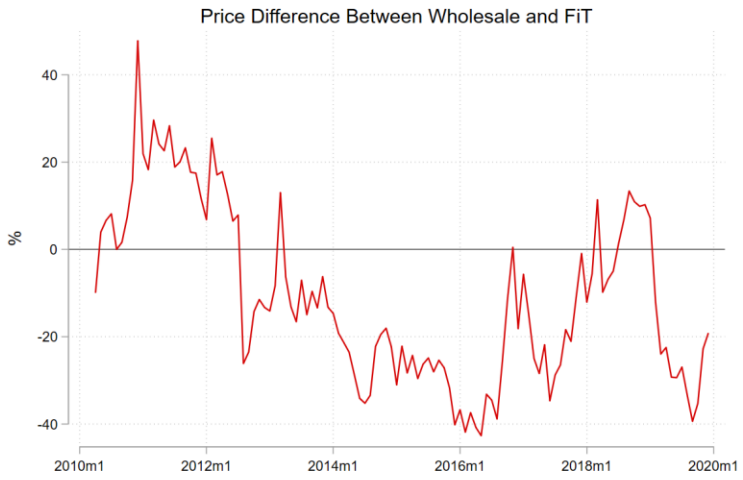


FIGURE 2. THE FIT EXPORT SUBSIDY

III. Theoretical Framework

I develop a simple partial equilibrium framework which explains generators' incentives to enter, wait and strategically downsize. It also 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 — Renewable energy generators are price-takers,[20] have zero marginal cost,[21] and decide on installed capacity (q_i) which determines their variable output (ηq_i), where η represents the capacity factor of the chosen technology and i

[20] 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).

[21] 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.

represents the generator. The "capacity factor" or "load factor" is a term used in energy economics to denote the ratio of actual electricity output over the theoretical maximum. For renewable energy, this ratio captures the impact of weather variability on realised generation.

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).[22]

Suppose the wholesale electricity price (p_t) that generators face is volatile and determined by the distribution $F(\mu_p, \sigma_p)$. Each generator has its project in a unique location which is associated with site-specific cost-shocks, $\chi_{it} \sim G(\mu_{i\chi}, \sigma_{i\chi})$.[23] Fixed costs are irreversible (i.e. they cannot be recovered if the project fails).

Fixed investment costs (I_{it}) are financed by borrowing. They increase in the installed capacity, electricity price volatility (which raises the cost of capital) and generator-specific cost shocks. I assume $I_{it} = g(\sigma_p)f(q)\chi_{it}$ where $g'(\sigma_p) > 0$, $f'(q) > 0$ and $g(0) = 1$. For expositional simplicity and without loss of generality, I model this 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). $f(q)$ drives how investment costs increase for a given increase in installed capacity, while $g(\sigma_p)$ captures the additional (scalar) increase in costs due to price volatility. This represents the cost of capital channel that is empirically documented for renewable energy projects and common to project finance where higher compensation is required for riskier investments (e.g. see Polzin et al. 2019, Steffan 2018, Section II.A). Using the observed bunching

[22] 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.

[23] 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.

behaviour, I place a lower bound on the value of $g(\sigma_p)$ to estimate the size of the volatility cost on investment (Section VII).

Firm Choice — In each period, generators decide whether to invest with or without policy support 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 (V_t^I) (see Equation 1):

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

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.

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

Intuitively, 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, q^f represents the optimal quantity of installed capacity, and $\bar{q}$ represents the FiT eligibility threshold.[24] The generator selects its project size subject to the FiT constraint.

$$\max_q V_t^{FiT} = \bar{p}\eta q_i^f + \sum_{s=1}^{\infty} \beta^s(\bar{p}\eta q_i^f) - I_{it}(\chi_{it}, \sigma_{\bar{p}} = 0, q_i^f) \;\; s.t. \;\; q_i^f \leq \bar{q} \tag{3}$$

[24] 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.

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.

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

Assuming a firm decides to invest in period t, its choice between investing with a FiT versus without it depends on whether $R_t \geq 0$, where $R_t \equiv V_t^{FiT} - V_t^I$ is defined below.

$$R_t \equiv \frac{\bar{p} q_i^f}{1-\beta} - q_i^I \left(p_t + \beta \frac{\mu_p}{1-\beta} \right) - \frac{\chi_{it}}{\eta} \left(f\left(q_i^f\right) - f\left(q_i^I\right) g\left(\sigma_p\right) \right) \geq 0 \tag{5}$$

Differentiating Equation 5, w.r.t. 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 B). 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 C.

If the export tariff ($\bar{p}$) is at least equal to the average wholesale electricity price, 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. If $\bar{p} \geq \mu_p$, then firms will enter with a FiT. A more formal exposition is presented in Appendix C, 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 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 value of 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 (for notational convenience, we will drop the capacity factors since they do not change the model dynamics and use $p^F \equiv \frac{\bar{p}}{1-\beta}$ and $\widehat{p_t} \equiv p_t + \beta \frac{\mu_p}{1-\beta}$).

$$p^F \bar{q} - \chi_{it} f(\bar{q}) = \widehat{p_t}(\bar{q} + \Delta) - \chi_{it} f(\bar{q} + \Delta) g(\sigma_p) \tag{7}$$

Solving Equation 7 for Δ^* which is the bunching upper bound and defining $\delta_c \equiv \frac{f(\bar{q}) - f(\bar{q}+\Delta) g(\sigma_p)}{f(\bar{q})}$ yields:

$$\Delta^* = \bar{q}\left(\frac{p^F - \widehat{p_t}}{\widehat{p_t}}\right) - \frac{f(\bar{q})}{\widehat{p_t}} \delta_c \chi_{it} \tag{8}$$

The upper bound (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.

We can solve for $g(\sigma_p)$ for inframarginal generators for an average firm (e.g. $\chi_{it} = 1$), assuming $f(q) = \alpha q$: [25]

$$g(\sigma_p)^{intensive} = \frac{\widehat{p_t}}{\alpha} - \left(\frac{p^F - \alpha}{\alpha}\right) \cdot \left(\frac{\bar{q}}{\bar{q}+\Delta}\right) \tag{9}$$

The value of volatility reduction to inframarginal generators is the forgone profit due to downsizing, taking into account the price differences. α reflects the marginal cost of production for an incremental increase in installed capacity. Empirically, α is declining over time due to exogenous technological progress.

However, there is also an *extensive margin* response to the FiT, where for certain generators $V_t^W > V_t^I$ pre-FiT[26] but post-FiT, $V_t^{FiT} > V_t^W > V_t^I$. Solving for $g(\sigma_p)$ in the same way we derived the Equation 9, gives us the value of volatility-reduction for the new entrants:

$$g(\sigma_p)^{extensive} = \frac{\mu_p}{\alpha} - \left(\frac{p^F - \alpha}{\alpha}\right) \cdot \left(\frac{\bar{q}}{\bar{q}+\Delta}\right) \tag{10}$$

This is also the forgone profit from selecting to enter at $\bar{q}$ but note, new entrants consider the expected wholesale electricity price, μ_p, instead of the observed period

[25] For the window of projects I am examining (e.g. around the 5 MW threshold) cost data on utility scale solar from NREL shows that costs increase approximately linearly with capacity. See: https://atb.nrel.gov/electricity/2021/utility-scale_pv#MIISNV9Q

[26] where, as shown in the appendix, in the absence of a FiT, $V_t^w = \beta \hat{V}^I$

electricity price. Using the model I can estimate (roughly) the value of volatility reduction: $g(\sigma)$ (Section VII).

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, 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.

IV. Data & Descriptive Statistics

A. Data

The Renewable Energy Planning Database managed by the UK Department for Business, Energy & Industrial Strategy (BEIS) 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 in the planning process, types of policy support, among other variables. It is a rich dataset which spans across decades and ends in 2021.

The database shows that there are 2,481 unique commercial solar projects in the UK, whose sizes range from 0.11 – 350 MW in installed capacity. The median and the mode for project size is 5 MW, while the mean is 9.3 MW. The second largest project is at 69 MW. Out of all solar project proposals, the status of 1,900 is known[27]

[27] 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.

from which 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.

Data on electricity prices is collected from Aurora Energy and data on solar panel costs is from Bloomberg New Energy Finance and NREL.

B. Descriptive Evidence

Between 2010-2019, nearly 1,600 commercial solar generators successfully entered the energy market, adding 12.5 GW of capacity. Many factors may explain why solar technology diffused in the UK, such as the reduction in solar panel costs (Figure A.5.), favourable macroeconomic conditions, and public demand for clean energy. However, one factor stands out: the UK's FiT policy.

As Figure 4 illustrates, the number of solar projects that apply for planning permission seems to trace changes in the FiT. The UK solar industry's beginning coincides with the introduction of the FiT in 2010. When the FiT export rate was increased by a third in 2012, there was a significant acceleration in entry, and in September 2015, when the Conservative Party announced plans to dilute and scrap the pre-accreditation process of the FiT, the entry rate plummeted. From a peak of 566 new proposed projects in 2015, there were only 32 new proposed projects in 2016 and 16 in 2017, a drop which goes against the declining cost of solar during that time.

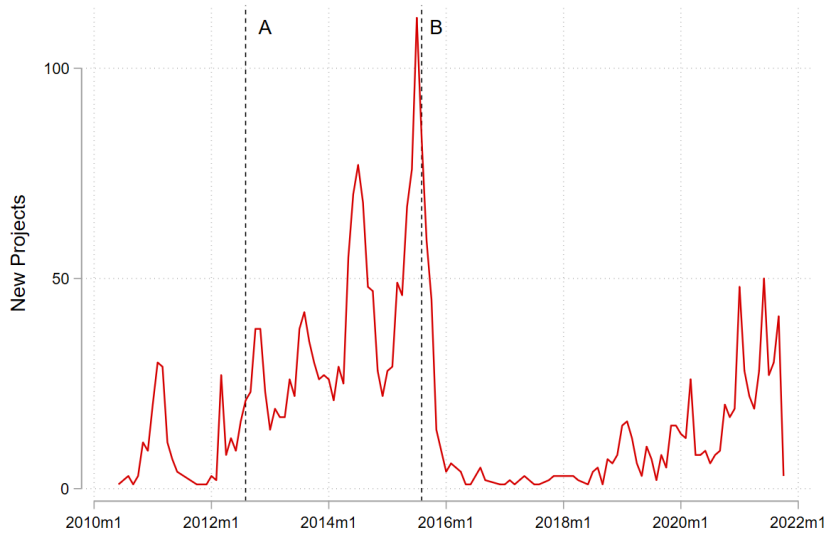


FIGURE 4. NEW SOLAR PROJECT PROPOSALS IN THE UK

Notes: data only displays commercial projects. Residential projects are not represented.

Solar project proposals started rebounding in 2018 but never returned to pre-announcement levels. This increase in 2018 is likely not driven by the FiT since plans to phase it out completely by the end of the 2019 financial year were clear. Instead, this moderate increase is likely to be illustrative of the fact that the solar industry matured as the technology developed and panel costs further declined (Figure A.3.). Lastly, Figure 5 demonstrates clear bunching behaviour around the 5 MW FiT eligibility threshold, an indication that the FiT policy had bite in shaping firms' behaviour. (A further bunch exists at 50MW. This is the threshold for Nationally Significant Infrastructure projects. Projects that are larger than 50 MW have a higher risk of being denied a permit as they are required to go through additional due diligence.)

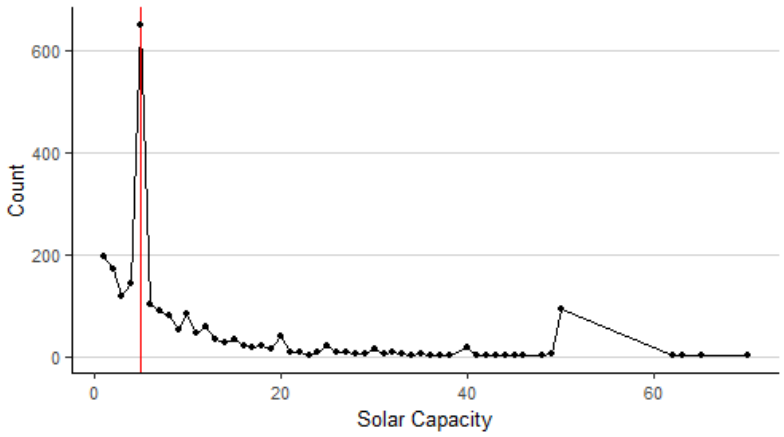


FIGURE 5. SELECTION AROUND THRESHOLDS LINKED TO LOWER RISK

Notes: Y-axis shows project count and x-axis shows capacity in MW

Overall, these trends suggest that the FiT may have played a large role in the diffusion of solar technology in the UK market. I conduct an event study to test this hypothesis more formally. However, caution should be exercised in interpreting these motivating results causally. While event studies can have causal interpretation, the assumptions required for this are strong and the paper presents these results in the context of descriptive evidence rather than causal evidence (Hausman and Rapson 2018).

C. Event Study

An announcement made by the newly elected Conservative Party in September 2015 removed guarantees that solar generators larger than 50 kW would get the export tariff upon entry. This guarantee, which is called "pre-accreditation", played an important role in assuring generators that they would benefit from the FiT prior to commissioning their installation.[28]

[28] The announcement also slashed the generation rates significantly but this primarily affected residential solar generation, which is outside the scope of this analysis.

The announcement was driven by an exogenous political event: the Conservative party won the elections in May 2015 and sought to reduce public expenditures across the board as per their Party's main line. A miscalculation in the budget resulted in further pressure to reduce expenditures.[29] Policy documentation and public consultations show that this announcement created strong beliefs that FiT would be scrapped, and in practice, the changes in pre-accreditation were tantamount to this (DECC 2015b). Therefore, I consider observations preceding September 2015 as "treated" (i.e., in a world with the FiT) and those after the date as "untreated" (i.e., in a world with no FiT/ highly diluted and inaccessible FiT).

Using a Poisson specification which is well-suited to count data, I examine how the number of new solar project proposals changes in the months after the announcement. This is done simply using time dummies from the announcement date. As Figure 6 shows, there is a statistically significant and sizable decline in entry rates in the months following the announcement.

However, one could ask if other variables are changing around this window of time. In the months immediately before and after September 2015, factors such as GDP growth and the cost of borrowing are smooth. Furthermore, over this period solar panel costs are decreasing, which if anything would suggest more entry rather than less. A final concern is if changes in the Renewables Obligation (RO) scheme[30] are driving observed results. However, plans to incrementally phase out the RO scheme by 2017 were announced in 2011, and generators would have accounted for this. By contrast, the FiT announcement is a shock as evidenced by the public consultation records and responses that followed the announcement.

[29] Due to gas price increases and higher than predicted load factors for wind power, that overall budget for energy was overshot and cuts had to be made across the board.

[30] The Renewables Obligation scheme gives RO-accreditation to low-carbon generators which allows electricity suppliers to buy from these generators to meet their mandatory quota of sourcing clean electricity.

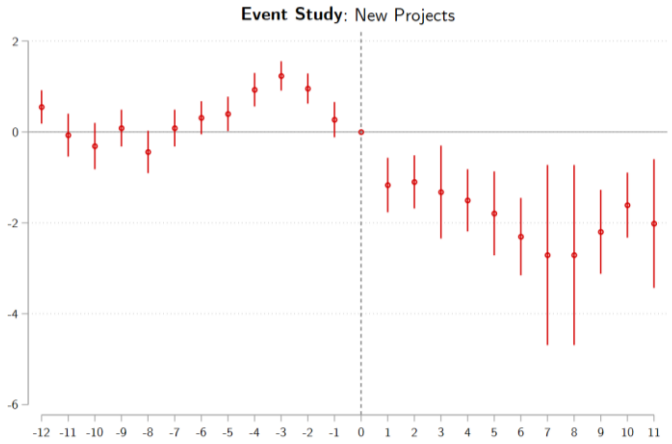


FIGURE 6. EVENT STUDY PLOT OF MONTHLY DECLINE IN NEW SOLAR PROJECTS

Another descriptive measure is to see how the announcement affected investment size i.e. installed capacity. Since the FiT is only applicable to projects less than or equal to 5 MW, we would not expect generators to enter at, or downsize to, the 5 MW threshold if the scheme has been effectively scrapped. As Figure 7 shows, once expectations took hold that the FiT would be highly diluted from 2016 onwards, project size did increase. There are, however, large uncertainties around these estimates due to the significant decline in the total number of new project proposals following the announcement, which results in a loss of statistical power.

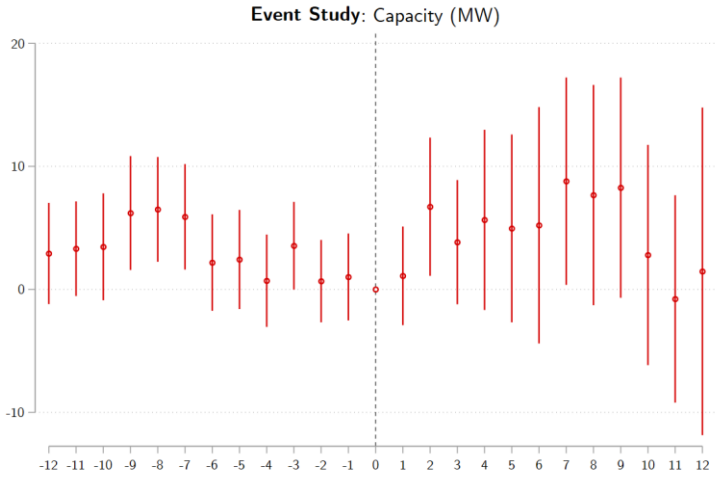


FIGURE 7. CHANGES IN THE SIZE OF NEW PROJECTS

V. Bunching Estimation

This section discusses my primary empirical strategy for causally identifying the impact of the FiT. I exploit the presence of discontinuous incentives to estimate the impact of the FiT on entry and investment in the solar market using a bunching estimator.

The FiT creates a sharp discontinuity at 5 MW (i.e. "notch") where generators below the threshold are eligible for the export tariff while those above the threshold are subject to fluctuating wholesale electricity prices. There is a strong behavioural response to the FiT, as evidenced by the significant amount of bunching around the 5 MW threshold (Figure 5). This response most likely includes generators that were planning to build more than 5 MW of capacity who downsize to take advantage of the scheme (inframarginal generators) as well as generators that previously had no intention to invest who enter the market thanks to the policy (marginal generators). In my empirical strategy, I will be disentangling these two responses to understand whether the FiT resulted in net capacity gains (as suggested by entry) or net capacity losses (as suggested by downsizing).

Conditional on no other discontinuous changes at 5 MW threshold, I can identify the causal effect of the FiT. To the best of my knowledge, there are no other policies which create discontinuities at 5 MW except for one: In July 2015, the government announced that the Renewables Obligation (RO) scheme would no longer be open to solar PV generators under 5 MW. This scheme gives accreditation to low-carbon generators so that electricity suppliers can source from them to meet their mandatory clean electricity quota. However, this is very unlikely to be a threat to identification because: (i) my results are primarily driven by incentives before the announced change to the RO scheme, since post September 2015 the removal of the FiT pre-

accreditation process led to the collapse of the scheme and a 86% drop in entry rates resulting in significant sample size reductions (see dynamic bunching, Section V.D.) and (ii) if the RO policy change had large effects, I would observe a collection of mass just *above* 5 MW since firms would upsize to be RO-eligible. I do not see this in the data for any time period. Thus, the bunching estimator should meet the identification conditions for a causal estimate.

I define an area around the 5 MW discontinuity where the behavioural response to the FiT occurs, which I refer to as the "exclusion zone" (q- to $q+$). Data outside the exclusion zone is used to estimate relationship between project count and capacity, which is extrapolated to the bunching area to create a no-FiT counterfactual (Chetty et al. 2011, Kleven and Waseem 2013).

The difference between the no-FiT counterfactual and the (with-FiT) observed data tells us the "excess mass" due to the policy. The difference between the observed data and the counterfactual after 5 MW and up to $q+$ gives us the "missing mass", which is the amount of capacity lost due to strategic downsizing. The amount of capacity that is due to new entry is the difference between the excess mass and the missing mass. In this context, strategic upsizing is not expected since all projects less than or equal to 5 MW can benefit from the FiT.

I first conduct a pooled bunching estimation over the whole time period (2010-2019). In the dynamic bunching section, I estimate the excess mass separately based on different export tariffs. The latter helps me see how much of the entry is driven by the "subsidy effect" since I have variation in the extent to which the FiT was a subsidy in expectation.

The main bunching estimation is:

$$(16) \qquad c_j = \sum_{i=0}^{n} \gamma_i \left(q_j\right)^i + \sum_{r \in N} \rho_r \cdot 1[q_r] + \sum_{i=q-}^{q+} \psi_i \cdot 1\left[q_j = i\right] + v_j$$

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 (which determines the shape of the fitted line between capacity and number of projects at that capacity), $[q\text{-}, q\text{+}]$ 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 16 omitting the contribution of the dummies around the notch (third term) but keeping the contribution of round-number dummies (second term).

Deciding appropriate values for $[q\text{-}, q\text{+}]$ is not an exact science. One way to get a first approximation is to exclude observations at 5 MW and fit a smooth local polynomial to create a rough no-bunch counterfactual. Where the counterfactual line intercepts the observed lines represents the start and end of the behavioural response (see Fig. A.7). The assumption is that the deviation of the observed line from the counterfactual line is due to the discontinuity at 5 MW, and where the two intersect is when the effect of the discontinuity ends. Since in my setting, there is no incentive to upsize, we are interested in the upper bound at which projects will be indifferent between downsizing to take advantage of the FiT and staying at their chosen capacity. Fig. A.7. suggests the behavioural response to the FiT ends at 6.2 MW. To be conservative, I will select an upper bound above this to bias results in favour of over-estimating the inframarginal response. I further present estimates for different values of $q\text{-}$ and $q\text{+}$ and polynomial choice. In every case there is a stable, highly significant, and large behavioural response due to the FiT, which is primarily driven by entry (see Appendix D for alternative specifications).

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 less of a 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.

A. Main Results

This section presents the results from estimating Equation 16, where the exclusion zone is $[q- = 4.8,\ q+ = 6.4]$, capacity bins are defined in terms of increments of 0.1 MW and a 4^{th}-order polynomial is used. These values provide a counterfactual that very closely fits the observed data outside the exclusion zone.

There is a significant and large bunching response at the FiT threshold, with 520 extra projects[31] at 5 MW relative to a counterfactual in which there is no FiT (Figure 8).[32] Around 6% of projects would be located elsewhere in the distribution in the absence of the FiT. These are the *inframarginal generators.* The remaining 94% are new entrants (see Figure 8, where bunching mass B minus missing mass M, gives the amount of new entry). This means that relative to a scenario with no FiT, there are *at least* 43 times more projects thanks to the FiT, leading to net capacity additions worth 2.3 GW (for context this is roughly equal to one-fifth of all installed solar capacity in 2021 in the UK). My estimates are local as they can only identify the effect of the FiT causally in a small window around the eligibility threshold.

[31] The total number of commercial solar projects from 2010-2019 is 2,500.

[32] There is another policy, the Renewables Obligation scheme, which is targeted at generators > 5 MW and accredits these installations so that suppliers can source from them to meet their mandatory quota of low-carbon power. However, if this policy were the driving force, we would expect bunching in the opposite direction. Instead, results show that generators are bunching towards the FiT. Moreover, the RO scheme was introduced well-before the FiT in 2002. However, the solar industry in the UK only started in 2010, with the introduction of the FiT.

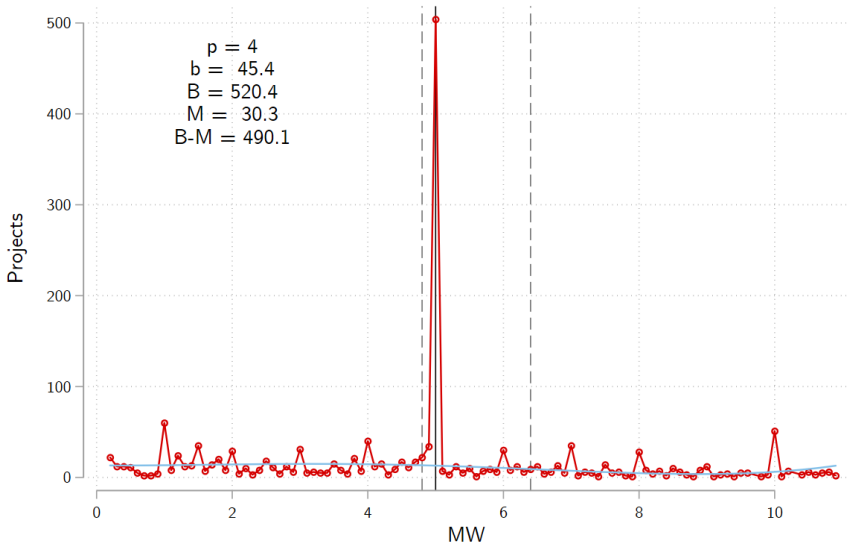


FIGURE 8. MAIN BUNCHING ESTIMATION

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.

The large extensive margin response is also reaffirmed by the difference between predicted and actual levels of installed capacity for a given level of solar irradiance. Figure 9 plots the *predicted* relationship between installed capacity and solar irradiance (which is obtained using observations outside the exclusion zone) and the *observed* relationship. It shows that around 5 MW of installed capacity, *predicted* solar irradiance is higher than *observed* solar irradiance. This is contrary to what we would expect if the FiT's effect was mostly in terms of downsizing as that would lead to many projects that are *too small* relative to their site's solar irradiance.

Lastly, one may question whether there is "cheating" whereby projects that are, for example, 10 MW, are instead classifying themselves as two separate 5 MW projects while effectively functioning as one larger project. I can test this directly in the data by seeing the distance between all 5 MW projects. Only 20 of 511 projects (3.9%) have identical locations, raising suspicions that they might be cheating. Even in these cases, 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.

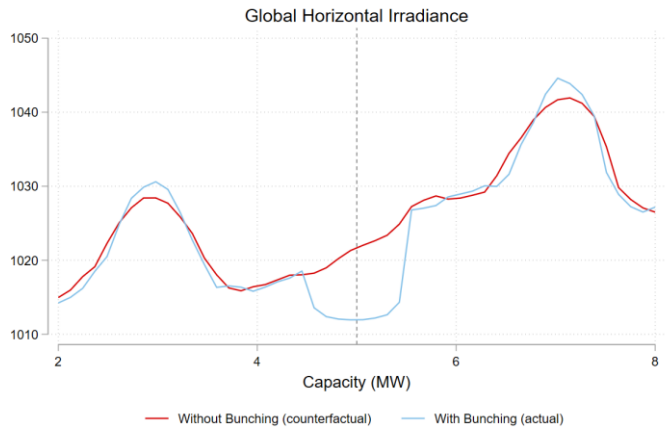


FIGURE 9. PREDICTED VS. ACTUAL CAPACITY IN SOLAR IRRADIANCE

B. Dynamic Bunching & Isolating the Volatility Effect

I leverage changes in the FiT tariff relative to the expected wholesale electricity price to see how the extent to which the FiT is an *expected* subsidy affects bunching (Figure 2 shows the *realised* extent to which the FiT is a subsidy in each period). This helps disentangle the effect of an instrument type from its "stringency" or "strength" (Polzi et al. 2018). Not all FiTs are equal: some give much larger subsidies than others, and even the same FiT can change in its subsidy-level over time, as I document.

There is significantly more bunching between August 2012 to August 2015 relative to April 2010 to July 2012 and post-2016 (see Figure 10). For convenience, I order the periods in chronologically and call them phase 1, phase 2 and phase 3.

Suppose firms form their expectation of future wholesale electricity prices based on the previous year's observed average. In phase 1, the FiT acts as a tax between 2011 to July 2012 as generators expect to lose £2.5-8.5/MWh by entering with a FiT. In phase 2, the FiT rate is always higher the expected market rate in all periods. The

expected subsidy ranges from £3.4 – 8.2/MWh. In phase 3, although the FiT is an expected subsidy, the pre-accreditation which assures generators of a guaranteed tariff before entering the market is removed, leading to practically no response to the scheme in this period (see Figure 10).

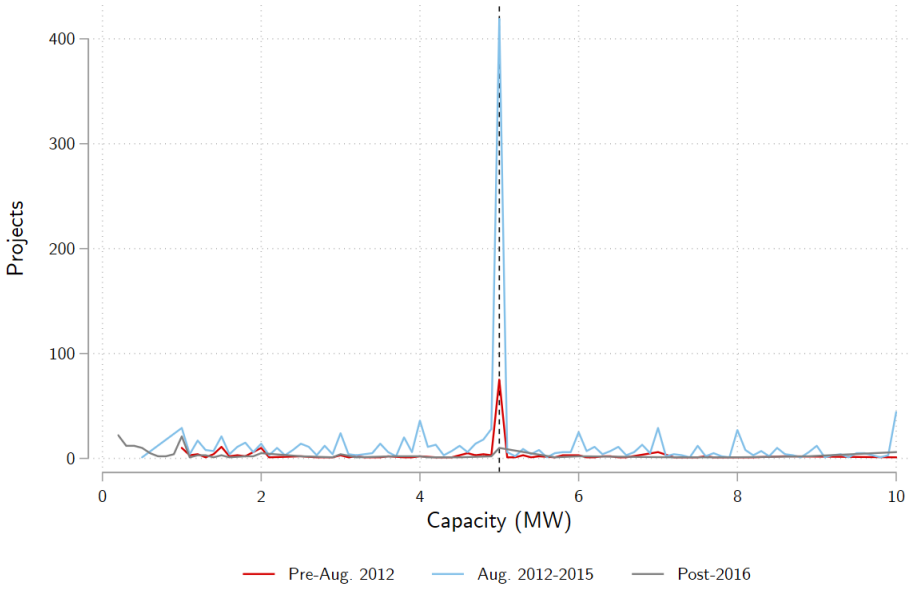


FIGURE 10. BUNCHING OVER DIFFERENT PERIODS OF TIME

The dynamic bunching estimates presented in Figure 11 and 12 show that there was, unsurprisingly due to the large subsidy, significantly more bunching during phase 2 relative to phase 1. In both cases the inframarginal response (M) is very small relative to the extensive margin response (B-M). In the phase 1, there are at least 27 times more projects relative to a no-FiT counterfactual. In phase 2, there are at least 41 times more projects. This difference is driven by changes in the extent to which the FiT is a subsidy in expectations.[33]

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

Perhaps most interestingly, even when the FiT is not an expected subsidy, there is *still* significant bunching at the eligibility threshold. I interpret a key reason for this is the volatility effect, which reduces investment costs.

One could argue that during the first and second FiT phases other variables apart from the export tariff changed, and that these factors may have affected the relative amount of bunching instead. 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. Only changes across time at the FiT eligibility threshold are a concern to the dynamic bunching identification and interpretation.

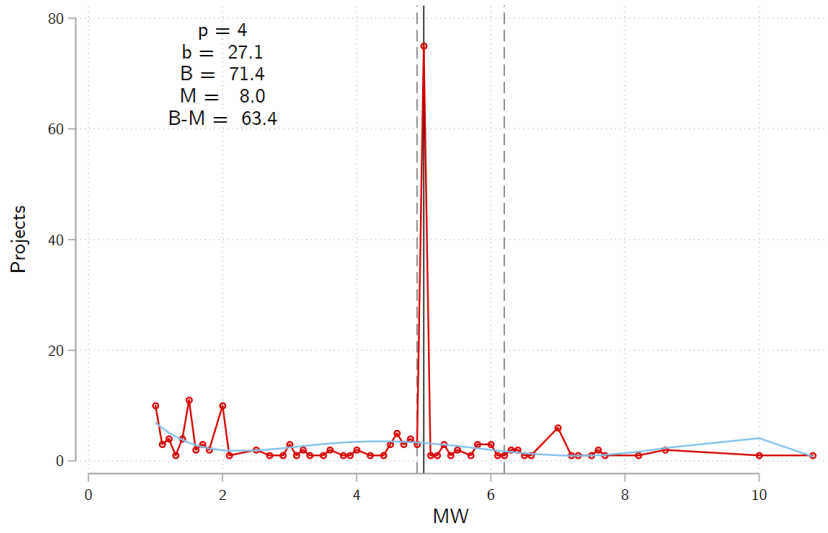


FIGURE 11. BUNCHING FROM APRIL 2010- JULY 2012

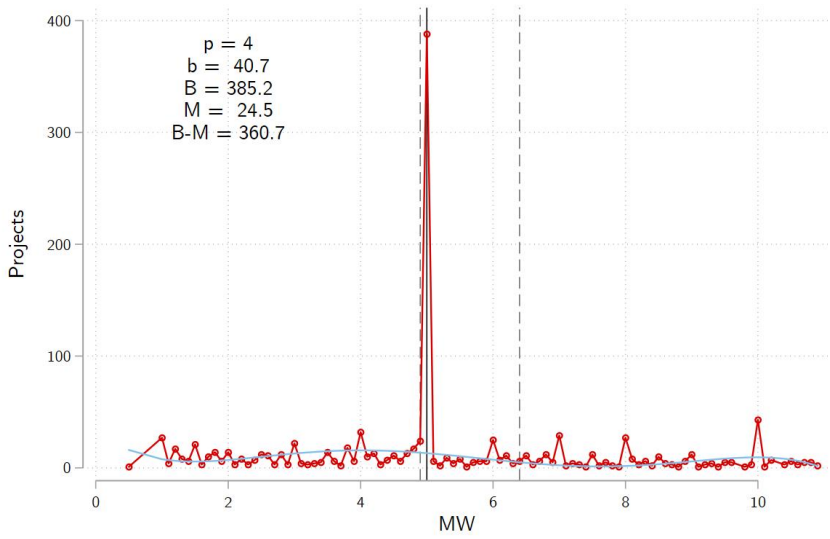


FIGURE 12. BUNCHING FROM AUGUST 2012 - AUGUST 2015

In sum, firms significantly value the FiT and bunch around the eligibility threshold, even in periods when the policy does not offer a subsidy in expectation, indicating that there is value to the pure volatility-effect of the FiT. However, when the FiT provides a subsidy benefit on top of the elimination in price volatility, the amount of bunching increases substantially.

VI. Dose-Response Estimation

The presence of bunching demonstrates that firms valued the FiT. To broaden my analysis and further help with interpretation, I now proceed with a dose response estimation to examine how prices and volatility affect entry.

Due to solar energy's small market share (<2% in my sample), solar generators are price-takers in the electricity market and fluctuations in the wholesale price are taken as exogenous. This allows me to use the difference in the export tariff and wholesale price to estimate the effect of the "export subsidy" on entry and investment size. Similarly, using daily wholesale electricity price data, I can calculate monthly volatility and use this to estimate the "volatility effect" of the FiT. Recall that the

policy becomes more valuable in highly volatile conditions (see Section III, Theory). This is another way to disentangle the volatility effect from the subsidy effect.

I estimate a dose response relationship to see how the number of new solar proposals per month changes in the extent to which the FiT is a subsidy and the monthly volatility of wholesale electricity prices. I add both the export subsidy and self-consumption subsidy. See Equation 17:

$$(17) \qquad c_t = \beta_0 + \beta_1(\bar{p}_e - \tilde{p}_{t-1}) + \beta_2(\bar{p}_g - \tilde{p}_{t-1}) + \beta_3(\tilde{\sigma}_{t-1}) + X'B + e_t$$

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. $\tilde{p}$ and $\tilde{\sigma}$ reflect quarterly moving averages to capture the idea that firms gradually update their expectations over time using observed subsidy and volatility levels to make current period decisions. 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 wholesale 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 effect both wholesale prices and solar entry. For example, winter leads to more demand for heating which causes higher wholesale electricity prices and consequently, a lower subsidy. One could easily attribute the dip in new solar proposals to this effect. But this could be erroneous as winter separately may 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* (i.e., via a different channel) 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. Overall, however, it is difficult to conceptualize which shocks would affect wholesale electricity prices *and* separately affect solar project feasibility which are not already controlled for in my specification.[34] Under the assumption that such shocks do not exist, the dose-response estimates can be interpreted as causal.

	Pre-2016 Entry ≤ 5MW Poisson (I)	Pre-2016 Entry ≤ 5MW Poisson (II)
σ^p	0.00839 (0.1432)	0.26778* (0.15743)
Export subsidy	0.08462*** (0.0269)	0.08808** (0.03672)
Generation subsidy	0.03572 (0.0246)	0.03069 (0.02771)
Constant	Yes	Yes
Year fixed effects	Yes	Yes
Seasonality	No	Yes
R^2	0.29	0.34
N	64	64

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., post-2016 there were large drops in entry as shown in Figure 4 which makes estimation harder due to the loss of statistical power). This allows me to more precisely estimate

[34] As long as these shocks affect solar through the subsidy channel, it is not a threat to identification.

how the relevant generators' incentives were impacted due to changes in FiT subsidy and volatility levels.[35]

I find that a one GBP per MWh increase in the FiT export subsidy (mean: £9.50) leads to 9% increase in the number of solar proposals, and this effect is significant at the 5% confidence level (see Specification II). 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% 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. Model-based Estimations

Finally, to further elucidate firm choice dynamics and underlying mechanisms by which the FiT policy works, I can use Section III's framework. This helps elucidate the relative effect of volatility reduction (cost of capital channel), the expected subsidy, and solar panel cost declines on generators' incentives to enter under a FiT. While the preceding analysis was in the spirit of isolating cause and effect, this section will focus on how the various effects come together to impact incentives. However, given the simplicity of the model in section III, these results should be interpreted at illustrative, with the primary aim being to clarify intuition.

Recall Equation 10 which equates the value of entering with a FiT and to entering without it.[36] In this equation, $g(\sigma)$ is the value of how much higher investment costs

[35] This also gives an overall sense of what happens in the market since most of the activity is concentrated at or below 5 MW (see IV B).

[36] I focus on the extensive margin as that is of most relevance to my empirical setting.

must be due to volatility such that a firm is indifferent between bunching at the FiT threshold ($\bar{q}$) and choosing a higher capacity ($\bar{q} + \Delta$), given the difference in prices at both points. An interpretation of $g(\sigma)$ is therefore, the scalar by which investment costs need to increase at $\bar{q} + \Delta$ for a firm to *just* decide to locate at $\bar{q}$ (i.e., $g(\sigma)$ is a lower bound; the true added cost of volatility may be higher).

Using wholesale electricity price data and solar production cost data (excluding financing costs) which help estimate α, I obtain estimates for $\hat{g}(\sigma)$ as a function of Δ (Figure 13). Suppose $\hat{g}(\sigma) = \kappa > 1$ and bunching is observed. This tells us that the lower bound of the added cost of volatility is given by $\hat{g}(\sigma)$, e.g. the generator decides to locate at the FiT eligibility threshold because in a non-FiT scenario investment costs are scaled up by a factor $\kappa > 1$ due to price volatility. Note that if no bunching is observed then the true cost of volatility is lower than $\hat{g}(\sigma)$.

Prior to 2012, when the FiT was not a subsidy and considerable bunching was still observed, I find estimates of $\hat{g}(\sigma)$ in the range of 1.05 to 1.2 (Figure 13). This indicates that in these years, generators locate at 5 MW if the investment costs are 5-20% higher without the FiT.

However, after 2012, I interestingly find that $\hat{g}(\sigma) \leq 1$, which means that a generator chooses to locate at the FiT threshold even if under a non-FiT scenario investment costs are *lower*. This counterintuitive result occurs because the subsidy effect greatly dominates post-2012 and is so large, that it flips the expected direction of that $\hat{g}(\sigma)$. This limits my ability to bound the added cost from facing volatility at higher capacities during this period in my sample.

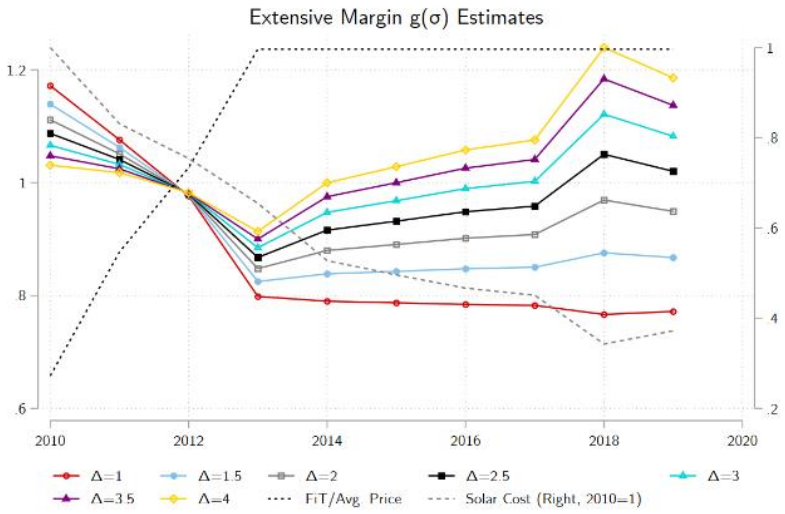


FIGURE 13

Furthermore, note that $\hat{g}(\sigma)$ changes depending on our assumptions of Δ, notably becoming higher as Δ increases. This indicates that as the foregone capacity increases, the investment cost differential between a non-FiT and FiT scenario must be greater to justify locating at the FiT threshold. This makes intuitive sense since a larger Δ reflects more forgone peak generation.

Lastly, despite the subsidy staying flat from 2013 onwards, my estimates for $\hat{g}(\sigma)$ steadily increase. This is due to the observed decline in solar costs, α. Intuitively, as solar costs fall, the value of downsizing to remain under the FiT threshold diminishes.[37] Thus, for bunching to be observed, the value of $\hat{g}(\sigma)$ must be higher to justify downsizing. Given a fixed FiT threshold and exogenous technological progress, a corollary of my simple model is therefore that the observed amount of bunching should decline over time. This offers some suggestive evidence that the added cost from price volatility is more constraining in earlier stages of technological deployment

[37] ...if the solar cost decline is more rapid than any price decline (which is not observed as long-run average wholesale prices exhibit no clear trend).

if we believe there are strong learning-by-doing externalities that may drive down technological costs.

VIII. Value for Money

To close my analysis, I consider whether the FiT represented value for money given the policy's objectives. The FiT scheme has two design elements: a fixed tariff for electricity exported to the grid and a generation tariff for electricity generated for self-consumption (i.e. "self-generation" which supports primarily households). The cost to electricity suppliers from the former is the difference between the export tariff and the wholesale price multiplied by FiT-accredited generation. For the latter it is the generation rate multiplied by the total quantity of FiT-accredited self-generation. For the years 2010 to 2019, the average subsidy for grid export was £6.5/MWh while the subsidy for self-generation it was significantly higher at £54/MWh. This difference along with the fact that self-generation accounted for 80% of all FiT-accredited power generation, show that self-generation accounted for the vast majority ($> 90\%$) of policy costs (Ofgem 2016; Ofgem 2019). A minority of policy costs can be attributed to the subsidization of FiT-accredited power for grid export which is the focus of this paper.

The figures in the FiT annual reports cannot be used to evaluate value-for-money in this paper because I focus on the causal impact of the FiT in a zone, around the 5 MW eligibility threshold, and because I do not consider the subsidization of electricity for self-generation. Therefore, I separately estimate the cost of providing the policy to the generators considered in this paper, and then compare that to the benefits from that generation.

I do a very simple back-of-the-envelope style calculation that uses the "local" causal estimates of net 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, where the cost is measured as explained above. UK-based capacity factors are used (see Appendix E 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, and this only considers the emissions-related benefits of the policy. For comparison, the lower bound estimates of the social cost of carbon from the literature are £60 t/CO2 (Pindyck 2018).

However, the government's objectives with the 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. Testing all of these aims formally is beyond the scope of this paper and presents a set of various empirical challenges, however some descriptive information is provided below.

First, given the prevalence of wind power in the UK, the FiT did help in energy-diversity as the main beneficiary was solar technology (Figure A.3). While the wind typically blows at night, solar is active during the day, making the two technologies useful together in terms of smoothing out intermittency, at least during summer months. There is still the consideration however, that in the UK, solar technology's capacity factor (11%) is far below that of onshore wind's (26%), which may mean that from a transitional perspective, wind is better.[38] Recall, however, that the FiT was also available to wind generation. There is a separate question of *why* solar became the main beneficiary, and in large part, I assume this is related to the modularity of the technology which allowed it to be placed on top of rooftops, find small-scale household and commercial applications, and have fewer requirements on

[38] See https://www.renewableuk.com/page/UKWEDExplained/Statistics-Explained.htm

land. One could do a more systematic analysis of this point but for the immediate question of whether the FiT helped improve the diversity of generation, the answer is yes.

Second, the government hoped to create more buy-in for the energy transition. While I do not have survey data on British attitudes towards low-carbon energy generation before and after the FiT, I can proxy this through the government's hypothesized channel: i.e., that by giving many agents across many regions of the UK a direct stake in the energy transition, they will be more supportive of it. I find that at least in terms of geographic reach, FiT solar is distributed widely across the UK (see Figure A.6). Since these projects require local council approval, a location with a FiT project is also an area where the community approved of its development. Insofar as project approval is an indicator of local buy-in, we can say that the FiT achieved good geographic reach (Figure A.6.).

Finally, one could hypothesise that the demand created by the UK FiT catalysed innovation and learning-by-doing externalities. Testing this formally is beyond the scope of this paper but other literature has shown these effects to be prominent. Gerarden (2022) uses methods in I-O and structural estimation to find that this is a commonly documented impact of FiTs, with the boost in demand due to FiTs resulting in higher solar panel efficiencies, and consequently, even greater diffusion beyond the first-order effect of the policy.

IX. Conclusion

This paper asks how nascent, socially-beneficial breakthrough technologies can be brought to market to meet social goals. This question is motivated by the hypothesis that due to credit market imperfections and unaccounted-for externalities, investment in clean energy is sub-optimally low. Using a bunching estimator, event study design, and dose response model, I find that the UK's renewable energy feed-

in-tariff (FiT) was highly effective in incentivising entry by low-carbon generators. This results in significant net low-carbon capacity additions. I find that effects are driven both by the embedded subsidy as well as the elimination of price volatility. I am able to disentangle the subsidy effect from the volatility effect using dynamic bunching, dose-response estimation, and a simple model calibration.

After estimating how much low-carbon capacity can be *causally* attributed to the FiT, I assess the scheme's cost-effectiveness via some simple value-for-money calculations. I find that a social cost of carbon ranging from 16-26 GBP/tCO2 is enough to make the policy a net gain.

More broadly, this work focuses on the role of risk-reduction in bringing breakthrough technologies to market which is a priority given the speed and scale at which economies must decarbonise to achieve net-zero emissions by 2050. While this paper conducts an empirical case study on solar energy, this broader question is likely to have relevance to other technologies such as green ammonia, long duration storage, and low-carbon materials, which are likely necessary to achieve agreed climate pledges.

In terms of limitations, this work concerns itself with case of policy for nascent breakthrough technologies, which occupy a small share of the overall market. My conclusions do not have external validity when applied to technologies with higher market shares. This is because the distortionary effects of volatility-dampening on overall market outcomes can no longer be approximated away. Specifically, in these cases, price volatility-dampening may lead to over or under-supply of electricity, and attenuate the incentive to invest in valuable technologies related to energy storage or demand-side response. Likewise, distortions in the credit market caused by the policy may skew other investments. In future work, it would be worthwhile to model the FiT in a full general equilibrium model with a credit market to be able to make

more general claims on optimal level of deployment, and conduct comparisons with other policies. This is a promising direction for future work.

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XI. Appendix

A. Figures

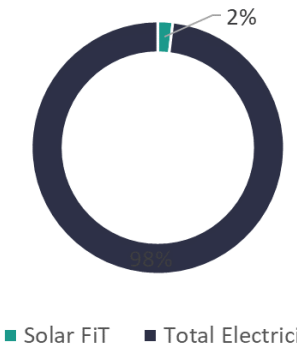


FIGURE A.1.. INSTALLED CAPACITY IN GB POWER MARKET 2011-19

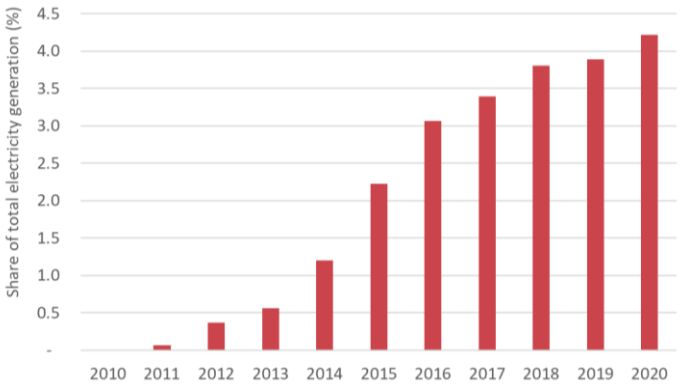


FIGURE A.2.. SOLAR GENERATION IN THE UK POWER MARKET

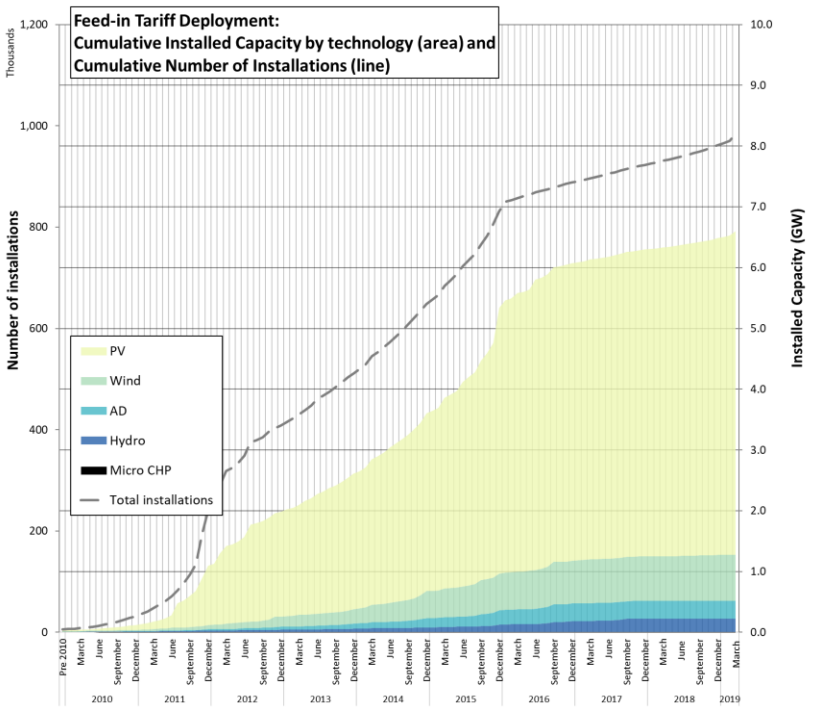


FIGURE A.3. RESIDENTIAL AND COMMERCIAL FIT ACCREDITED ENTRY BY TECHNOLOGY

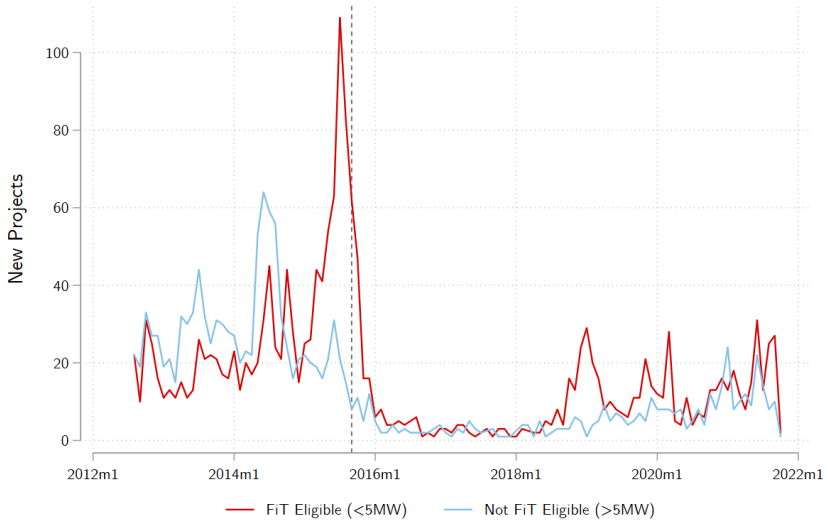


FIGURE A.4. NEW SOLAR PROJECTS BY FIT ELIGIBILITY

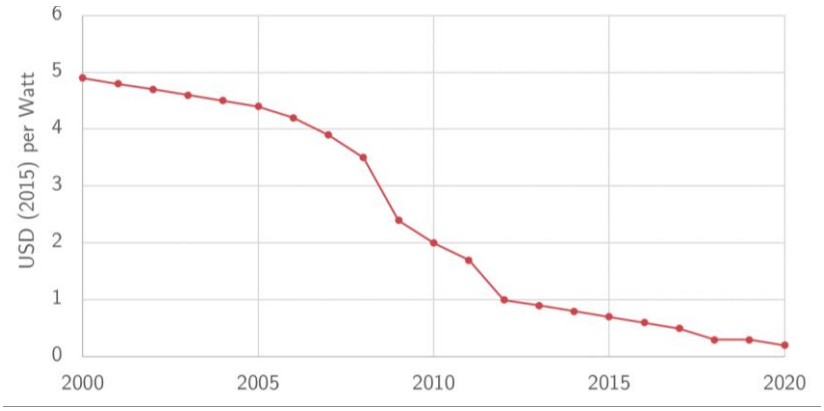


FIGURE A.5. SOLAR PANEL COSTS

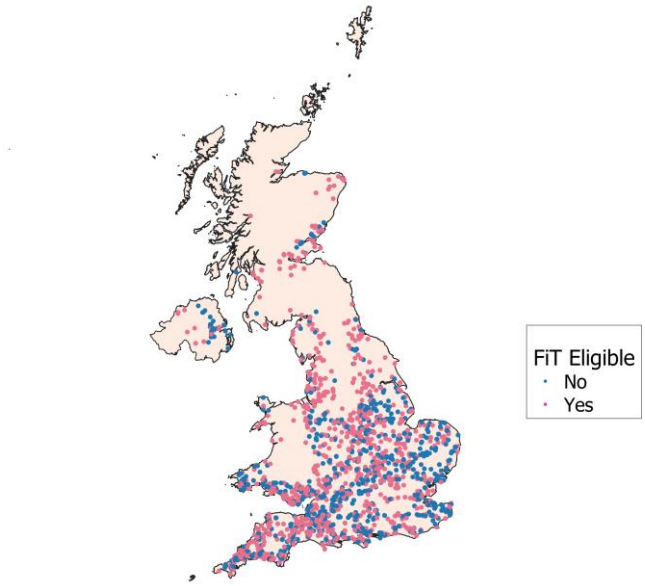


FIGURE A.6. SOLAR PROJECTS BY SIZE IN THE UK

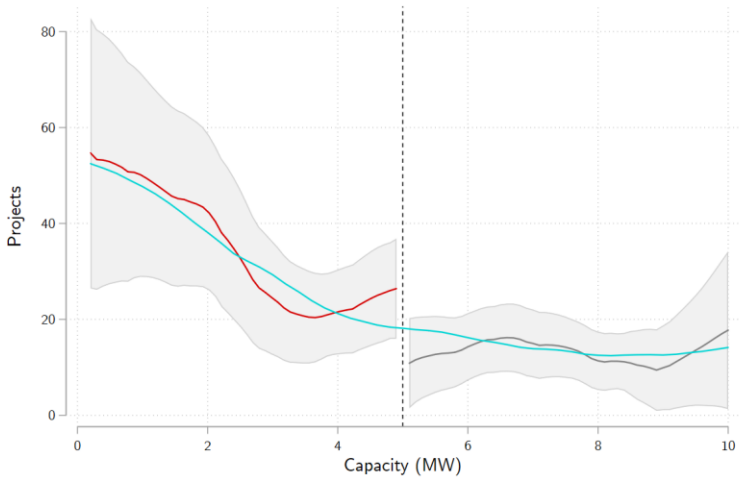


FIGURE A.7. ESTIMATING THE WINDOW OF THE BEHAVIOURAL RESPONSE

Notes: Blue line shows fitted polynomial for counterfactual distribution. Red line is pre-notch observations. Grey line is post notch observations.

B. Solving for the Wait Value Function

The value of waiting is given by Equation A.1

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

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

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

Note that in expectation, the choice of optimal installed capacity time across periods under a FiT is the same, that is $E_t q^{f*}_{t+1} = E_t q^{f*}_{t+2} = \cdots = E_t q^{f*}_{t+T}$. 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) $$\max_{q} V_t^w = \beta \max\{\hat{V}^{FiT}, \hat{V}^{I}\}$$

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) $$V_t^w = \beta \hat{V}^{I}$$

C. 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, $max\{\beta\hat{V}^I, V_t^I\}$. As σ_p increases, investment costs rise, and V_t^I decreases, as does $\beta\hat{V}^I$. A firm invests today if $V_t^I > \beta\hat{V}^I$, 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.

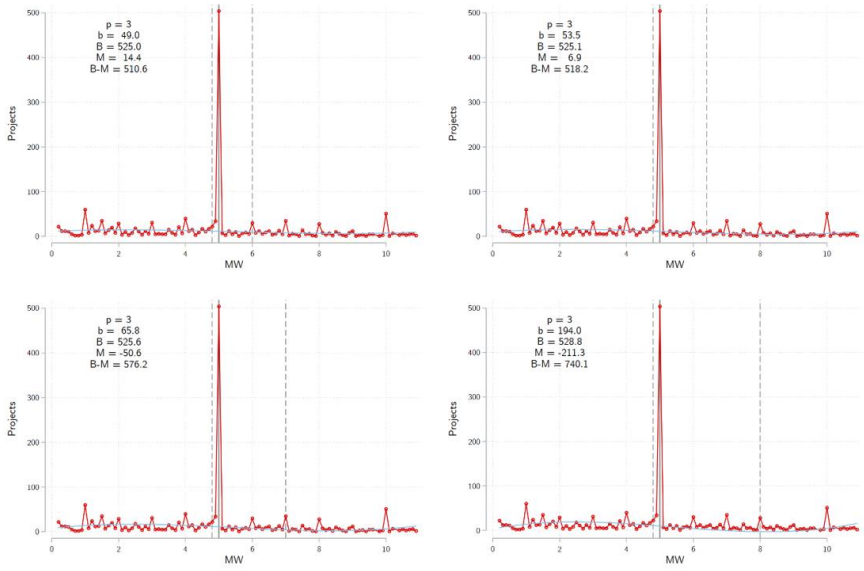
If there is a FiT, then given a sufficiently attractive tariff rate (which is at least equal to the expected average price of electricity), there is likely to be more entry today relative to a scenario where there is no FiT. V_t^{FiT} does not change in the volatility of the market price of electricity. 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 $\hat{V}^I$ 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 ($\beta\hat{V}^I$) and (ii) the discounted profit given the FiT rate and average cost shock ($\beta\hat{V}^{FiT}$). 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

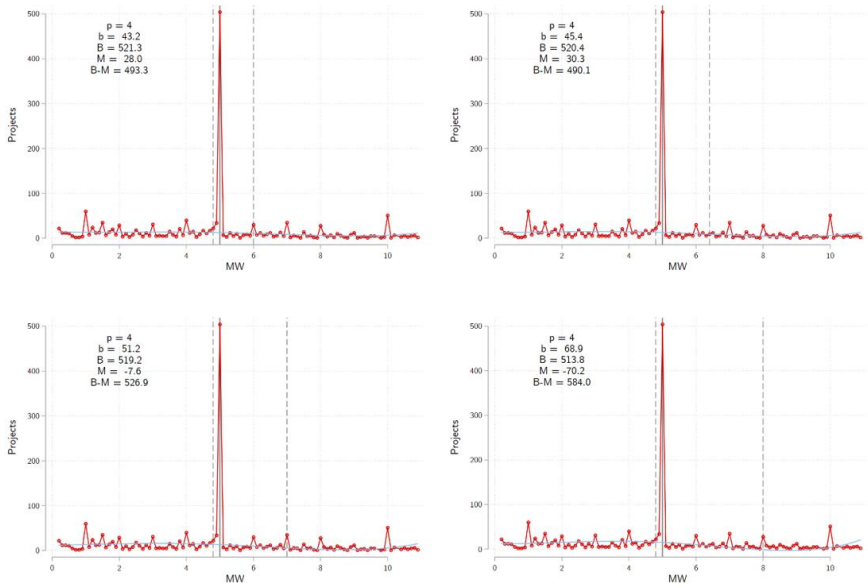
that when price volatility is high, the value of investing today with no support falls, while the value of investing with a FiT does not, and this means that there is a higher chance of entry in a world with FiTs.

D. Robustness Tests

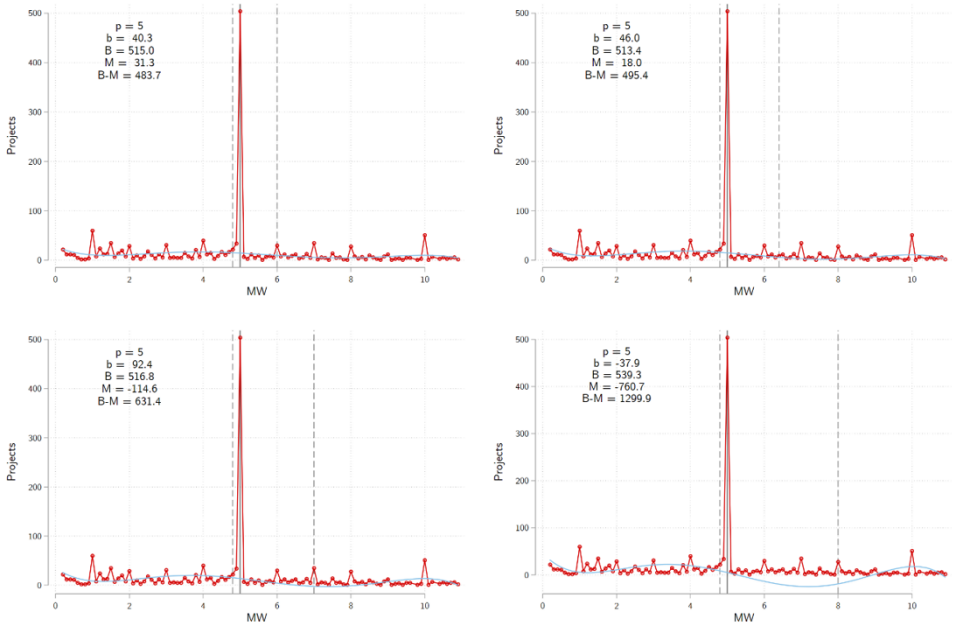
3rd-order polynomial: Lower bound = 4.8 MW, different upper bounds



4th order polynomial: Lower bound = 4.8 MW, different upper bounds



5th order polynomial: Lower bound = 4.8 MW, different upper bounds



E. Value for Money Calculations

Value for Money Calculations I - Upper Bound of Emissions Displaced		
Variables	**Values**	**Comments**
Net Capacity Additions due to FiT - MW	2,270	Obtained from bunching estimates
Solar Load Factor	0.11	UK Solar Load Factor
Days in a Year	365	
Annual Solar Generation due to FiT - MWh	91,141	Capacity*Days*Load Factor
Emissions intensity of energy displaced by solar - tCO2/MWh	0.40	
Emissions displaced by FiT Solar - tCO2	36,456	Generation*Emissions Intensity
Social Cost of Carbon - £	16.3	SCC at which annual benefit = annual cost
Annual value of emissions displaced by solar - £	592,413	Generation*Social Cost of Carbon
Net subsidy given to FiT accredited solar - £/MWh	6.5	Export tariff - wholesale electricity price (average value)
Annual cost of overall FiT solar subsidy - £	592,413	Generation*Subsidy
Annual cost less annual emissions benefit - £	0.00	

Value for Money Calculations II - Lower Bound of Emissions Displaced		
Variables	**Values**	**Comments**
Net Capacity Additions due to FiT - MW	2,270	Obtained from bunching estimates
Solar Load Factor	0.11	UK Solar Load Factor
Days in a Year	365	
Annual Solar Generation due to FiT - MWh	91,141	Capacity*Days*Load Factor
Emissions intensity of energy displaced by solar - tCO2/MWh	0.25	
Emissions displaced by FiT Solar - tCO2	22,785	Generation*Emissions Intensity
Social Cost of Carbon - £	26.0	SCC at which annual benefit = annual cost
Annual value of emissions displaced by solar - £	592,413	Generation*Social Cost of Carbon
Net subsidy given to FiT accredited solar - £/MWh	6.5	Export tariff - wholesale electricity price (average value)
Annual cost of overall FiT solar subsidy - £	592,413	Generation*Subsidy
Annual cost less annual emissions benefit - £	0.00	