Bringing Early-Stage Technologies to Market: Evidence from Utility-Scale Solar and Feed-in-Tariffs

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*By Sugandha Srivastav**

Incomplete markets and uncorrected environmental externalities result in the under-provision of low-carbon technologies. 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. Bunching disappears once certain risk-reduction guarantees are removed. A social cost of carbon equal to £100/tCO2 makes the policy a net benefit. Tradable certificates that provide similar subsidies are not able to induce the same degree of market-creation, illustrating the value of long-term price hedging for early-stage technologies.

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* University of Oxford. Email: sugandha.srivastav@ouce.ox.ac.uk. I would like to thank Gharad Bryan, Sarah Clifford, Tim Dobermann, Sam Fankhauser, Todd Gerarden, Richard Green, Cameron Hepburn, Francois Lafond, Stefan Lamp, Ashley Langer, Erin Mansur, Jacquelyn Pless, Stefan Pollinger, Mar Reguant, and Alex Teytelboym. I would also like to thank participants at the following spring/summer 2022 conferences: EAERE, TSE Economics of Energy & Climate, NBER Economics of Innovation in the Energy Sector, LSE Grantham, Oxford Economics Jamboree. Financial support is gratefully acknowledged from the Climate Compatible Growth Programme, INET Oxford, and the Smith School of Enterprise & the Environment. The support of Aurora Energy Ltd. which shared GB Power Market data is gratefully acknowledged. I also thank Ofgem and LCCC.

I. Introduction

To stabilise global mean temperatures, the world must achieve net zero emissions, a target that has now been widely adopted by most major economies (Net Zero Tracker 2022). Achieving net zero emissions will require the rapid introduction and diffusion of novel clean technologies. However, these technologies remain under-provided (Stern and Valero 2021), not only because of uncorrected environmental externalities but also because of incomplete information and incomplete markets.

For early-stage technologies, investors do not know the full range of contingencies that need to be insured against which creates incomplete markets for finance and insurance and increases the cost of capital. First-mover projects have an important "demonstration effect" as they help fill informational gaps about the distribution of risk and returns for the new technology, which helps in market creation and deepening, and reduces the cost of capital. For example, in 2010 in the United Kingdom (UK), there were almost no private risk hedging instruments for utility-scale solar since agents had never seen such a project operational in the country before (Speer, Mendelsohn and Cory 2010). When the government stepped in with a publicly provided risk-hedge, via the feed-in-tariff (FiT), the industry was born and subsequently, private markets for solar insurance and finance emerged. Nascent technologies often face a chicken and egg problem where finance is needed for a project, but it also helps to have a few projects running to get finance.

In this paper, I examine the effects of long-term risk hedges and subsidies on investment in low-carbon technologies with a focus on the utility-scale solar market, which went from being non-existent on the UK grid to accounting for 4.3% of total electricity generation in 2020 (BEIS 2020). Utility-scale solar is typically 3-4 orders of magnitude larger than rooftop installations and important for system-level decarbonisation (IEA 2021). Incomplete markets for finance and insurance have a particularly significant impact on utility-scale solar since projects are highly capital-intensive, project timelines are multi-decadal, and there are regulatory, market-based and technology risks, which create greater barriers to entry. Although solar is considered cheap today, it was commonly viewed as expensive and an unfeasible means to reduce power sector emissions less than a decade ago (The Economist 2014).

My empirical context is the UK's feed-in-tariff which reduces the risk associated with investing in clean energy by giving renewable electricity generators a guaranteed price at which their power will be bought over 25 years. To be eligible for the scheme, the generator's installed capacity must be less than or equal to 5 MW. Larger projects must contend with volatile wholesale power market prices or those of tradable clean energy certificates. Considerations related to risk are particularly important for solar generators sine they are price-takers in the energy market and unlike other forms of generation, they cannot manipulate when they produce electricity to take advantage of anticipated price spikes. They simply produce power when the sun shines. [1]

I develop a model where in each period, a solar firm chooses how much to invest and whether to wait or enter today, with or without the FiT. Investments are irreversible. The value of entering with a FiT increases in the volatility of electricity prices since the fixed tariff shields risk-averse agents from fluctuations ("volatility effect"). [2] It also increases in the difference between the fixed tariff and the expected market price, which is the "subsidy effect".[3] The model predicts bunching at the FiT eligibility threshold. Some generators that would have entered at larger capacities in a no-FiT world strategically downsize to take advantage of the FiT. This represents lost solar capacity and carbon abatement. It also predicts entry thanks to the policy which represents additional solar capacity and carbon abatement.

[1] Solar generators with battery storage are able to choose when to dispatch power. However, during my time period of analysis, battery storage was not common.

[2] The FiT can also reduce revenue volatility by ensuring that it is easier to sell units of power. For simplicity, I only focus on price volatility.

[3] It is possible for the fixed tariff to be *below* the wholesale electricity price.

I use project-level data from 2010-2019 from the UK's Renewable Energy Planning Database. This dataset has a record of all clean energy projects in the country. My time period of analysis covers the start of the UK utility-scale solar industry to the present day. I conduct a bunching estimation similar to Kleven and Waseem (2013) where I define an area around the 5 MW threshold (the "notch") where there is a behavioural response to the FiT. Observations outside of this window are used to create a no-FiT counterfactual. The difference between no-FiT counterfactual and the with-FiT observed data gives us the "excess mass" due to the policy. Any hole/dip immediately towards the right of the notch represents the "missing mass" (generators that strategically downsized). The difference between the excess and missing mass reflects the amount of new entry/net capacity additions.

I find that the FiT had a highly significant and large impact on solar deployment. Relative to a no-FiT counterfactual, there are at least 43 times more commercial utility-scale solar projects thanks to the FiT, resulting in 2.3 GW of additional solar capacity over a period of five years (2010-2015), which is equal to one-fifth of all solar capacity today.[4] Only 6% of projects are inframarginal due to strategic downsizing and the remaining 94% are new entrants (i.e., majority of the response is on the extensive margin). In terms of absolute numbers, there are at least 490 new utility-scale commercial solar projects due to the FiT (for context, the total number of commercial solar projects from 2010-2019 is 2,481). Estimates are lower bounds due to the local nature of the estimation. Furthermore, when the FiT is heavily diluted in 2016, bunching at 5 MW completely disappears, suggesting that the earlier bunching is indeed driven by the FiT as opposed to other factors that might differ at the 5 MW threshold.

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

While the extensive margin effect leads to additional solar capacity relative to a no-FiT counterfactual, the cut-off in the FiT rate may have introduced inefficiencies relative to a FiT with no cut-off.[5] If there are economies of scale to solar development, then the accumulation of new projects at 5 MW is inefficient. However, any potential inefficiencies are likely to be limited due to evidence that the cost curve for solar is U-shaped with diseconomies of scale starting somewhere between 5 – 10 MW. This is driven by step-changes in land permitting costs and congestion costs. The latter is linked to accommodating ever-larger generators on a transmission and distribution network that is fixed in the medium term.[6] Furthermore, I do dynamic bunching to show that in post policy periods, there is hardly any entry at larger capacities – if there were, this would raise larger concerns about efficiency losses from extensive margin bunching during FiT years (Figure 9).

Since the FiT acts as a subsidy in addition to being a risk-hedge, both characteristics of the policy could be driving the results. I isolate the value of risk reduction by looking at periods when the price offered by tradable certificates is similar to that offered by the FiT. This happens roughly between 2012 to 2015. I find that, in this period, the vast majority of firms still enter at the FiT cut-off. While the tradable certificate provides the same subsidy in that period, it is much more risky as the price can change due to fluctuating market conditions. This illustrates how there is a tension between market-based schemes that have dynamic efficiency but more risk (Ciarreta, Espinosa and Pizzarro-Irizar 2014), and interventions that forgo this efficiency like FiTs but provide stable incentives. For

[5] Pollinger 2021 considers kinks in the German FiT and how the participation margin (i.e., the extensive margin response) affects structural estimates of elasticity. However, in this paper, I will not be estimating the elasticity structurally since at the notch, two variables are changing: subsidy level and exposure to risk.

[6] In the UK, congestion on the grid is a major problem with many new projects having to wait for significant periods of time to secure a grid connection (Call for Evidence on Onshore Solar, 2022, UK Parliament).

early-stage technologies, the results of this paper suggest that the presence of long-term risk hedges is critical for entry and investment.

Finally, analysis of relative bunching over different periods shows that bunching peaks when expectations take hold that the FiT will be diluted, even though the subsidy is sizably lower in this period. I can observe firms' expectations through regular documentation on public consultations between government and the solar industry. This suggests that when firms expect the policy would stay, they are strategic about whether they enter this period or next. Waiting has value because of persistent declines in the cost of solar panels (learning-by-doing externalities). However, when faced with the prospect that the FiT will be removed, and there will no longer by any type of long-term risk hedge, many generators advance their decision to enter the market. This likely explains why bunching peaks in 2015.

To develop a sense of whether the benefits of the FiT outweighed the costs, I undertake simple value-for-money calculations by comparing the benefit of the FiT in terms of displaced carbon dioxide and sulphur dioxide emissions against the cost of payments in excess of the market price of electricity (i.e., the subsidy amount). I do this only for the years in which I have real data rather than for the entire 25 year contract period, which would involve forecasting future power system prices. I find that the FiT leads to a net gain for society with a social cost of carbon of £100/tCO_2 and higher.

In this paper, I focus on the role of risk reduction to incentivise entry and investment in nascent, capital-intensive technologies which relates to a rich literature on real options (Dixit and Pindyck 1994, Aguerrevere 2003, Boomsma et al. 2012, Kellogg 2014). The empirical context is utility scale-solar. The intersection of risk and clean technology investments has also been explored empirically by Ryan (2022) who shows how counterparty risk has a bearing on renewable investments in India.

While this paper conducts an empirical case study on solar energy, the broader question on the role of risk reduction in bringing early-stage 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 generate positive externalities and, face uncertainty, risks, incomplete information and credit market imperfections.

More broadly, this paper builds upon an emergent literature that seeks to go beyond the carbon externality when examining the market failures that affect the transition to a low-carbon future (e.g. Jaffe et al. 2005, Van Benthem, Gillingham and Sweeney 2008, Acemoglu et al. 2012, Pless and Srivastav 2022, Gerarden 2022). So far this literature has primarily focused on how knowledge spillovers affect the clean transition. I expand this by considering the issue of incomplete markets and the role of (temporary) publicly provided risk hedges, such as FiTs, in bringing clean technologies to market.

Specifically, this paper provides novel estimates of the effects of FiTs, and in particular price risk reduction, on entry and investment in utility-scale solar. The majority of the empirical work on economic incentives for solar focuses on rooftop solar (e.g. Cherrington et al. 2013, Grover 2013, Germeshausen 2018, Pollinger 2022), where the agents analysed are households rather than firms, and the installation size, upfront investment, and project horizon are orders of magnitude smaller. This creates a very different economic environment. Rooftop solar studies focus on factors relevant for households such as: peer effects (Bollinger and Gillingham 2012 and Graziano and Gillingham 2015), private valuations over new technology (Langer and Lemoine 2022), household discounting (De Groote and Verboven 2019, Talevi 2022) and self-consumption (McKenna, Pless and Darby 2018). 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).

This work, by contrast, focuses on firm behaviour and the themes of uncertainty, incomplete information, and higher cost of capital. This paper also touches upon (i) the efficiency costs of policy thresholds, (ii) the effect of learning-by-doing externalities on increasing the value of waiting and how the temporary nature of policy support can counteract this waiting dynamic to induce entry, and finally, (iii) the effect of solar subsidies. Methodologically it connects to the bunching literature that leverages notches (e.g., Kleven and Waseem 2013, Kleven, Landais and Søgaard 2016, Best and Kleven 2018), but is different from most studies since the observed bunching is driven primarily by new entry rather than strategic downsizing.

The rest of this paper is structured as follows: Section II details the institutional context by discussing the design of the FiT, the UK solar industry and the general policy environment, Section III presents the theoretical framework to motivate why bunching may occur, Section IV overviews the data and presents some descriptive statistics, Section V discusses the empirical strategy and results, Section VI calculates the FiT's value for money, and finally Section VII concludes.

II. Institutional Context

A. Feed-in-Tariff Design

The UK has a target to achieve a zero-carbon power grid by 2035. Prior to 2010, there was no utility-scale solar in the country. The FiT, introduced in April 2010 and phased out by April 2019, provides a fixed price for electricity generated and sold to the grid by a renewable energy generator which is less than or equal to 5 MW in size. The price is guaranteed over 20-25 years.[7] Solar photovoltaics, wind, hydro, anaerobic digestion, and micro combined heat & power are all eligible.[8] All electricity generated receives the "generation tariff" and that which is exported to the grid receives an additional "export tariff". For solar farms that export 100% of their electricity, which is vast majority of utility-scale farms, the effective fixed tariff is the sum of the generation and export tariffs which is adjusted for inflation each year. In early years, the tariff is 8 times higher than the market price of power while towards the end of the sample, it is roughly equal to it. Solar panel costs also decline over this period (see Figure 1).

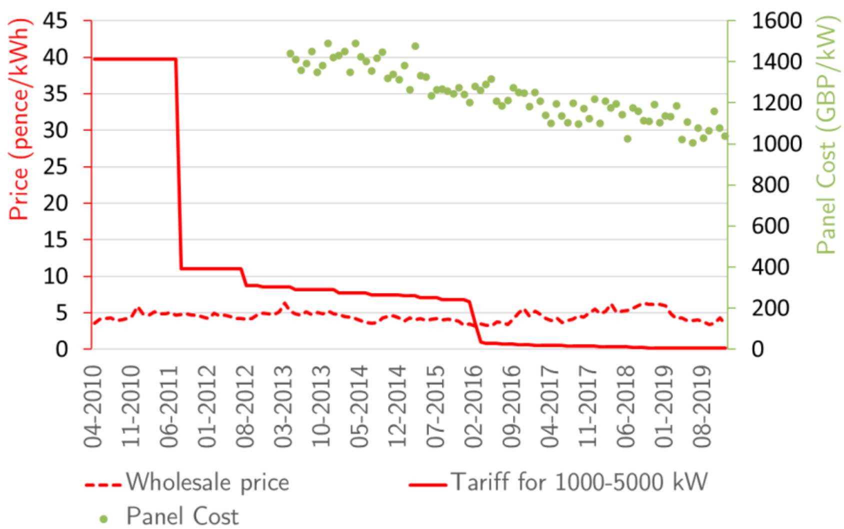

FIGURE 1. FIXED TARIFF VERSUS THE MARKET RATE OVER TIME

During the first half of the FiT's implementation period, it was the one of the main risk hedging instruments on the market. Corporate power purchase agreements (PPAs) for solar energy were extremely scarce, as were insurance products (see Figure 2; Speer, Mendelsohn and Cory 2010). FiTs provided off-the-shelf guarantees

[7] The contract duration for all technologies except for solar is 20 years. Solar benefits from 25 year contracts. Presumably this was to encourage diversification.

[8] Micro combined heat & power had a different eligibility threshold due to its smaller size.

that a new renewable energy generator's power would be purchased. In the absence of the FiT, these generators would have had to negotiate power purchase agreements with utilities and incur the transaction costs as well as the risks linked with brokering such a deal (if it was ever reached).[9]

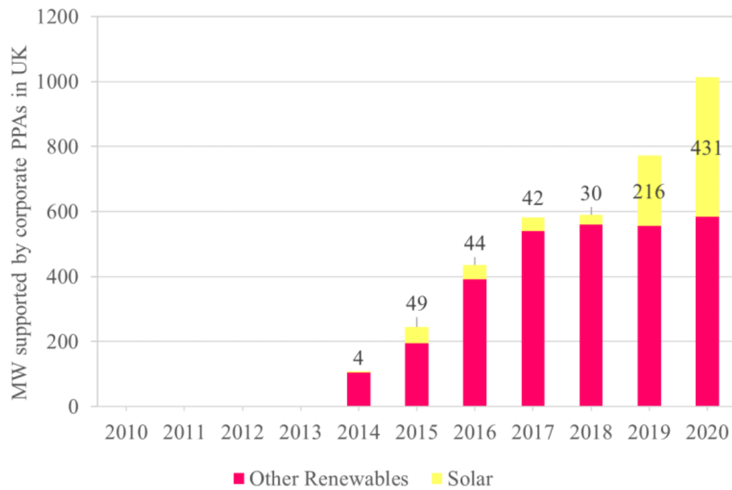

FIGURE 2. POWER PURCHASE AGREEMENTS IN THE UK

Notes: RESource 2022

In terms of how the scheme was financed, electricity retailers made payments to accredited FiT generators at the specified tariff. The extent to which the tariff exceeded the wholesale electricity price reflected the cost, which was passed onto to consumers through bills. The government set a cap on annual FiT-related payments. Once this cap was hit, additional installations entered a queue and could be considered when the cap reset.

B. Background on Solar

Although solar panels are more commonplace today, they were regarded as expensive and risky technologies back in 2010 (Figure A.1 in Appendix). Utility-scale solar projects contend with long project horizons (>20 years), volatile wholesale

[9] Based on author's interview with a private renewable energy developer.

electricity prices, and uncertainties in the due diligence and permitting processes. These factors affect the cost of capital which makes up a significant portion of overall project costs (Steffen 2020).

Investor guidance reveals how in the early-days of solar, an "offtake agreement" was a pre-requisite to get any sort of financing (Groobey, Pierce, Faber and Broome 2010). Such agreements could take the form long-term power purchase agreements with utilities (if available) or feed-in-tariffs. Higher project risk translated into a higher cost of capital due to risk aversion by investors (Polzin et al. 2019). Often risk could not be fully diversified away due to unknown elements of the early-stage technology. Solar projects typically had no recourse to the parent corporation's balance sheet or credit worthiness, and the only collateral available to financiers was the renewable energy asset and its expected future cash flows (Steffen 2018). I hypothesize that the FiT helped induce investment because it demonstrated a stream of guaranteed future returns by offering a fixed price at which power would be sold, which in turn reduced the cost of capital and helped more firms enter the market. This is tested empirically in Section V.

C. Policy Environment around the Cut-Off

The UK introduced its Renewables Obligation (RO) scheme in 2002 which required electricity retailers to source a certain amount of their power from renewable energy generators. The sourcing could be done through the purchase of tradable renewable obligation certificates (ROCs). The RO formally closed to all new generating capacity in March 2017. Unlike the FiT, the RO did not reduce price risk since ROC prices could fluctuate according to demand and supply conditions. However, like the FiT, the RO did offer a subsidy, which at certain points in time, was similar in value to the FiT (see Figure 3, 2012-2015). At or below the 5 MW threshold, generators could qualify for the FiT but if they opted for it, they would need to relinquish the ability to claim ROCs.

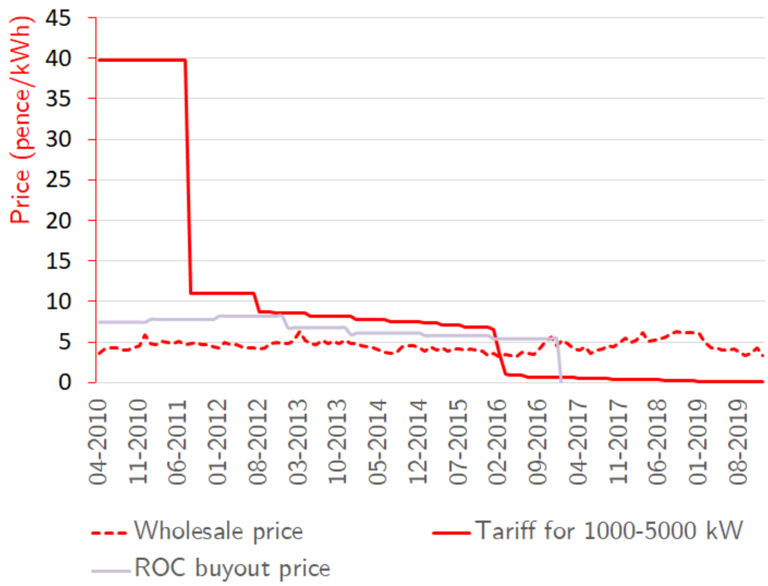

FIGURE 3. WHOLESALE POWER PRICE, FEED-IN-TARIFFS AND PRICE OF ROCS

III. Theoretical Framework

A. The Model

The Environment — Solar generators are price-takers,[10] have zero marginal cost,[11] and decide on installed capacity (q_i) which determines their variable output (ηq_i) where η represents the capacity factor and i, the generator.[12] Generators cannot manipulate the quantity of electricity they produce as this depends on exogenous weather conditions. They can, however, select their installed capacity, which

[10] Renewable energy generators' electricity production is driven by exogenous weather conditions and cannot be strategically manipulated.

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

[12] The capacity factor is the ratio of actual electricity output over the theoretical maximum. For solar energy, this captures the impact of weather variability on realised generation.

determines their maximum output. I assume generators know their own capacity factor (Kellogg 2014), meaning that the havey access to reasonable weather predictions that can provide an indication of what the expected monthly capacity factor for a given project and location may be.

The electricity price is volatile, $p_t \sim F(\mu_p, \sigma_p)$. Each generator is in a unique location which is associated with site-specific cost-shocks, $\chi_{it} \sim G(\mu_{i\chi}, \sigma_{i\chi})$. These costs depend on factors such as topography, distance from grid, land licensing costs, etc. 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. This 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. 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.

The impact of σ_p on investment costs represents how higher compensation is required for riskier investments. This is an empirically documented fact for renewable energy projects and can be conceptualised in terms of risk aversion by investors (Byoun et al. 2013, Steffen 2018, Polzin et al. 2019).[13] I assume risk cannot be fully diversified because of fundamental uncertainty over the probability distribution of risks as is expected for early-stage technologies.

Firm Choice — In each period, generators decide whether to invest with or without the FiT, or wait. This choice is the maximum of the value of waiting (V_t^w), the value

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

of investing today with a FiT (V_t^{FiT}) and the value of investing today without any risk-hedging (V_t^I) (see Equation 1):

(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. V_t^w is solved recursively in Appendix A.

(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 their expected values. If the value of entering today is lower than the value of entering in the future, a generator will choose to wait.

The value of V_t^{FiT} is given by Equation 3, where $\bar{p}$ represents the tariff guaranteed under the FiT, q^f represents the optimal quantity of installed capacity, and $\bar{q}$ represents the FiT eligibility threshold.[14] The generator selects its project size subject to the FiT constraint.

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

V_t^I is given by Equation 4, where q^I represents the optimal quantity of installed capacity. The price at which power is sold, p_t, is variable. Note, a generator can enter at $q \leq \bar{q}$ and choose to not opt for the FiT, therefore there is no constraint.

[14] 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.

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

Assuming a firm decides to invest in period t, its choice to enter with a FiT depends on whether $R_t \equiv V_t^{FiT} - V_t^I > 0$.

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

Higher price volatility and tariff favour entry with the FiT ($\frac{\partial R}{\partial \sigma_p} > 0$, $\frac{\partial R}{\partial \bar{p}} > 0$), while a higher expected wholesale electricity price/ROC price favours entry without a FiT ($\frac{\partial R}{\partial \mu_p} < 0$).

B. Model Predictions

Proposition 1: Timely Entry — Assuming there is volatility in the market price of electricity, if the tariff is at least equal to the average electricity/ROC price ($\bar{p} \geq \mu_p$), then there more timely entry with a FiT relative to a world with no FiT.

Proof of 1 — To see how, 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 without it 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.

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.

Proposition 2: Strategic Downsizing — Some generators who 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 *inframarginal generators* as they would have entered even without the FiT but decide to strategically downsize thanks to it (also known as the "intensive margin" response in the bunching literature).

Proof of 2 — 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:

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

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 increases with the monetary benefits of the FiT and decreases with its costs (Equation 6). Since $\frac{\partial\Delta}{\partial\sigma_p} > 0$, as volatility increases, generators will make bigger reductions in size to strategically benefit from the FiT. Δ is empirically important as it will define the area over which we will observe strategic downsizing.

Proposition 3: New entry due to the FiT — There is also an *extensive margin* response to the FiT, where the policy will induce new entry.

Proof of 3 — For certain generators $V_t^W > V_t^I$ in a world with no FiT[15] but after the introduction of the FiT, $V_t^{FiT} > V_t^W > V_t^I$. Empirically, by using a bunching estimator, I will determine the extent to which the FiT resulted in strategic downsizing versus new entry for different assumed values of Δ.

Proposition 4: Extensive Margin Bunching — A proportion of new generators will be constrained to enter at the FiT cut-off when they may have entered at larger capacities in a world where the FiT had no size-based threshold.

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

Proof of 4 — If the FiT were smooth, generators could enter at any capacity $\bar{q} + \Delta$,but since the FiT has a cut-off, some generators who would have found it optimal to select a larger size will be constrained to entering at $\bar{q}$ (details in Appendix).

Proposition 5: Entry induced through temporary support — If the FiT will be removed next period, some generators will advance their decision to enter the market.

Proof of 5 — If there are learning-by-doing externalities, a generator may find it preferable to enter with a FiT in a future time period, when the cost of solar panels is lower than the current period ($V_{t+1}^{FiT} > V_t^{FiT}$). However, if in the subsequent time period, there will be no FiT, then the generator may advance their decision and enter today if $V_t^{FiT} > V_t^I$.

C. Model Boundaries

This partial equilibrium model does not consider the distortionary effects of volatility reduction/price shielding on overall market outcomes. If FiT projects comprised a large share of the market, such distortions would be important to study (for example, generators could produce too much or too little power inhibiting market clearing). However, in the UK power market, solar is less than 2% of installed capacity, and FiT-accredited solar is less than half of all solar. Moreover, a single 5 MW project is far too small to influence prices in any way (the total power system size is 4 to 5 orders of magnitude larger). Therefore, these general equilibrium effects are assumed away. This paper is concerned with the role of FiTs for early-stage technologies that, by definition, have very low market shares.

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 and development process. It 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 from 2010 to 2019. The total number of clean energy projects across all technologies is 6,624.

The median and the mode for commercial solar 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.[16] 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. For the analysis, I assume a project "enters" when it applies for planning permission – this is the earliest date in the dataset. To ensure my results and analysis reflect actual added capacity, I filter out projects that subsequently backed out or were denied permission, leading to a sample size of 1,596 commercial solar projects.

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 since it operates as one zone. 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.[17]

[16] 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.

[17] 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.

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.

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

B. Descriptive Evidence

Between 2010 and 2019, 1,596 commercial solar generators successfully entered the power 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 that, there were no commercial solar projects.

The amount of new solar capacity steadily increases from 2010 to the end of 2015. The jagged structure of the plot reflects seasonality as each winter, the number of new solar projects falls. In 2016, there is a sudden drop in new capacity. This is when the pre-accreditation process of the FiT was removed.

The pre-accreditation process ensured that generators larger than 50 kW received a guaranteed tariff level before beginning construction. This guarantee played 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 tariff has changed and the project’s economics are no longer favourable.

An event study plot, which is presented in the spirit of descriptive evidence since confounding factors are not controlled for, illustrates how prior to the removal of the pre-accreditation process, there was an anticipatory increase in entry rates and how a month after the policy change, there is huge drop in new projects. Solar project proposals start rebounding in 2018 but never returned to previous levels. Sub-section C discusses the event study in more detail.

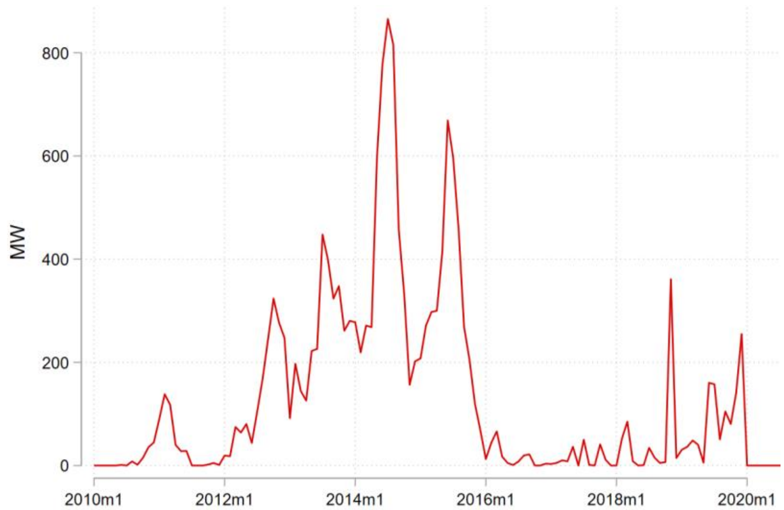

FIGURE 4. MONTHLY NEW COMMERCIAL SOLAR CAPACITY IN THE UK

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.

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 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.

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

As the event study plot 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.[18]

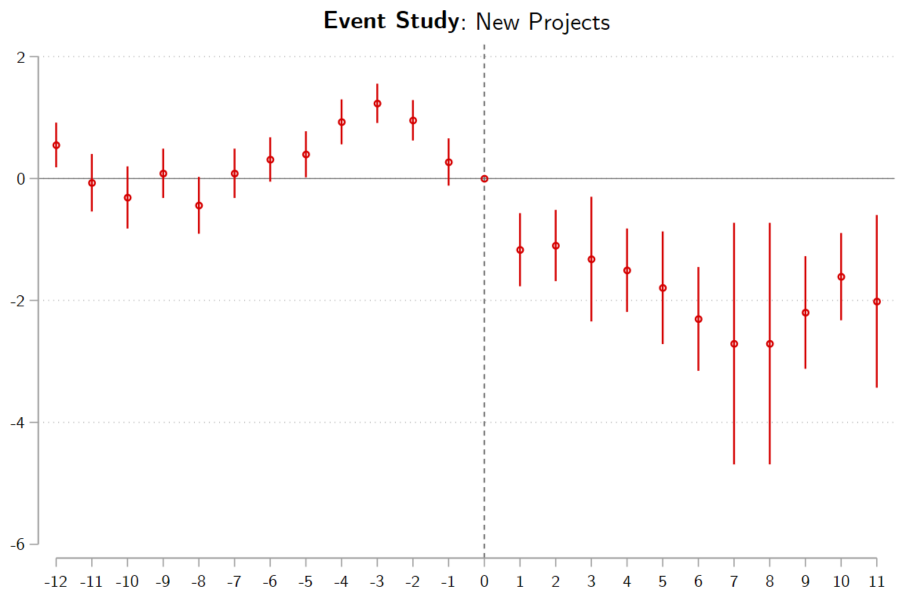

FIGURE 5. EVENT STUDY PLOT OF MONTHLY DECLINE IN NEW SOLAR PROJECTS

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. Section V will present the bunching estimation which is the main empirical strategy.

V. Bunching Estimation

A. Empirical Strategy

The FiT creates a sharp discontinuity at 5 MW (notch) where generators below the threshold are eligible for the fixed tariff while those above are subject to

[18] 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.

fluctuating wholesale electricity prices or ROC prices. I exploit this discontinuity to estimate the impact of the FiT on entry and investment in commercial solar.

Recall that firms can either wait, enter without any risk-reduction policy, 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 (new entry/extensive margin) versus those who switch from entering at higher capacities to downsizing and entering with a FiT (inframarginal/intensive margin). While new entry results in solar capacity additions which is helpful for decarbonisation, downsizing reflects lost capacity/abatement and support to inframarginal generators, which is inefficient.

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

The bunching estimation is found from the following model:

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

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 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 (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 bunching estimation creates a local no-FiT counterfactual and compares 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 to the right of the notch. The amount of new entry is the difference between the excess mass and the missing mass.

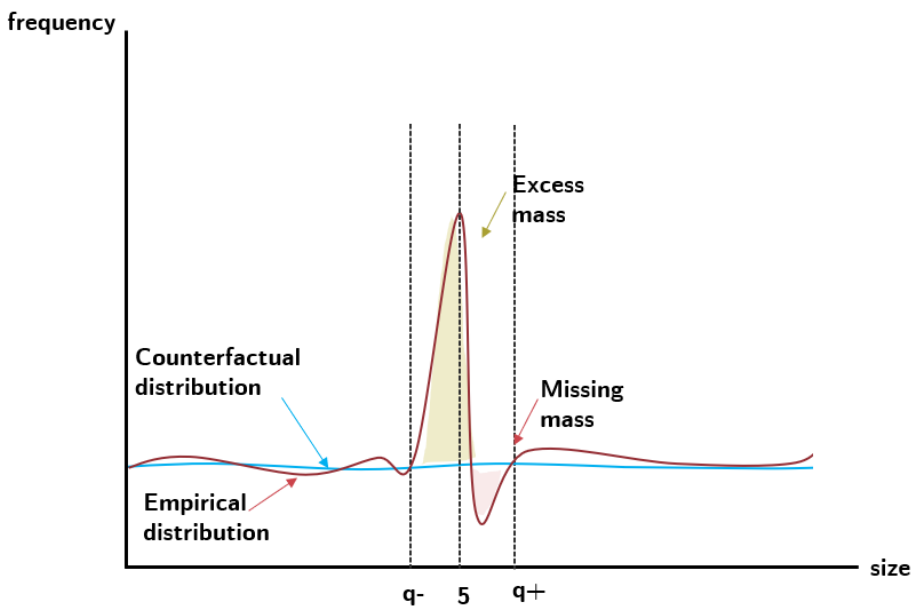

FIGURE 6. SCHEMATIC OF BUNCHING ESTIMATION

Deciding appropriate values for [q-, q+] is subjective: 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- is 4.9 since many firms mistakenly think the eligibility criterion is a strict inequality. In settings where the response is entirely on the intensive margin, 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.

In the baseline specification, I assume $q+ = 6.5$ MW. This choice is informed by a series of robustness tests that find that there is limited 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 Section V.E.).

Adjustment costs 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 discontinuities occur.

B. Identification Assumptions & Caveats

Identification via bunching at a threshold requires that there are no other policies or market features that could create incentives to invest in solar at the 5 MW cut-off apart from those created by the FiT (Kleven 2016). I explore this assumption by checking the empirical distribution of solar project size post-2016 when the FiT was highly diluted. There is no observable bunching anymore, suggesting that this main identification assumption holds (Figure 7).

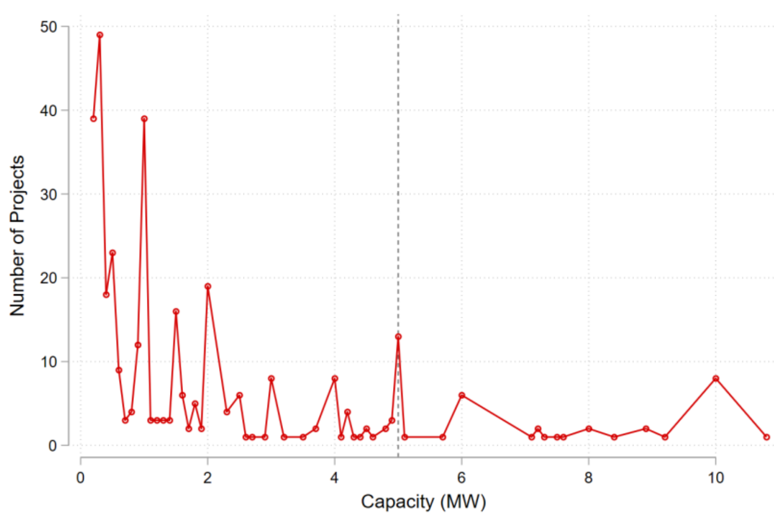

FIGURE 7. ABSENCE OF BUNCHING POST 2016

Notes: The small peak at 5 MW is the standard round number clustering.

Since observations below the notch still benefit from the FiT but are used to create a "no-FiT" counterfactual, the approach likely under-estimates the true effect. An alternative is to estimate the counterfactual only using observations to the right of the notch outside the excluded zone. However, this brings its own set of challenges — these projects may serve as a less valid control group since larger projects may have different economic characteristics relative to smaller ones. It also results in the loss of statistical power. Therefore, I choose to over-estimate the level of the counterfactual distribution and produce a lower-bound estimate of entry and capacity additions due to the FiT.

I also assume the marginal solar project does not influence prices in the power market. If the marginal solar project affected prices, firms' decisions would not only consider the change in financial incentives at the 5 MW discontinuity but also expectations of how other solar generators would react to it. For example, if one project's entry depressed prices, this would impact the next project's calculation of expected profits. This would contaminate our interpretation of the effect of the discontinuity. However, it is reasonable to assume a single 5 MW solar project does not affect prices as it is extremely small compared to the total UK power market, which is 4-5 orders of magnitude larger.

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. Results with lower and higher order polynomials are reported in Section V.E. but since the data outside the notch is relatively flat, it is unlikely that higher order polynomials are needed.

There is a significant and very large bunching response at the FiT threshold (Figure 8). 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 commercial, utility-scale solar energy. Visually, it is 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.

Taking into account the capacity lost from strategic downsizing, I find there are *at least* 43 times more solar projects thanks to the FiT, leading to net capacity additions worth 2.3 GW (equal to one-fifth of all installed solar capacity in the UK using 2021 figures).[19] In terms of absolute numbers, there are at least 490 new utility-scale commercial solar projects due to the FiT (for context, the total number of solar projects from 2010-2019 is 2,481). As noted earlier, these estimates are likely lower than the true effect because there could be more entry driven by the FiT below q- that the estimator is unable to capture.

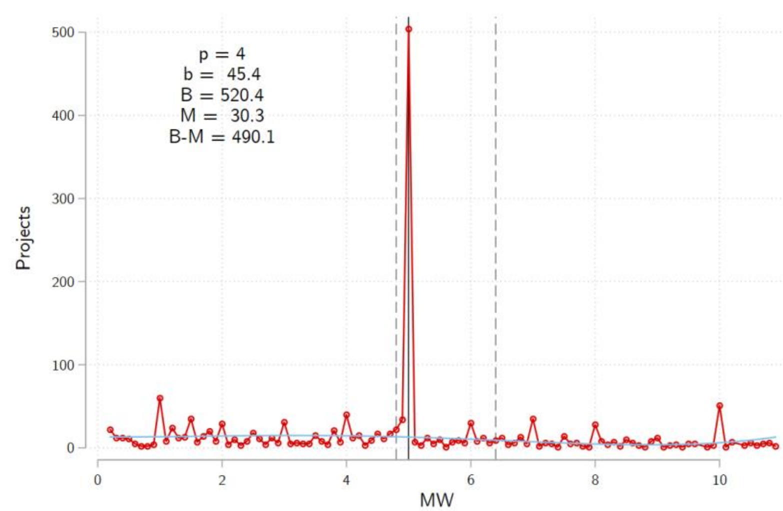

FIGURE 8. MAIN BUNCHING ESTIMATION

[19] 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.

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.

D. Differences in Bunching

Examining how the extent of bunching changes over time can shed light on how the changing characteristics of the FiT affect firms' incentives. Figure 9 plots the histogram of project size over the last decade. From this descriptive evidence, one can see that bunching peaks in 2015, right before the heavy dilution of the FiT scheme. This aligns with the evidence presented in the event study (Section IV.C) as well as the theoretical predictions that there will be expedited entry by generators if the FiT will be removed, since those who were previously deferring entry to take advantage of learning-by-doing externalities, now find it more advantageous to enter with a FiT today than to lose the option to have the risk hedge in the future (Section III.B).

Furthermore, concerns related to efficiency losses due to extensive margin bunching can be partially allayed, not only by considering the cost curve for solar which is U-shaped, but also by the fact that post-2016, when there is effectively no FiT, there is no significant entry at higher capacities. If after 2016, there were many projects at higher capacities, this would raise concerns that during FiT years, entry was artificially constrained at 5 MW. Instead, it seems like the FiT played a key role in creating that entry and market itself.

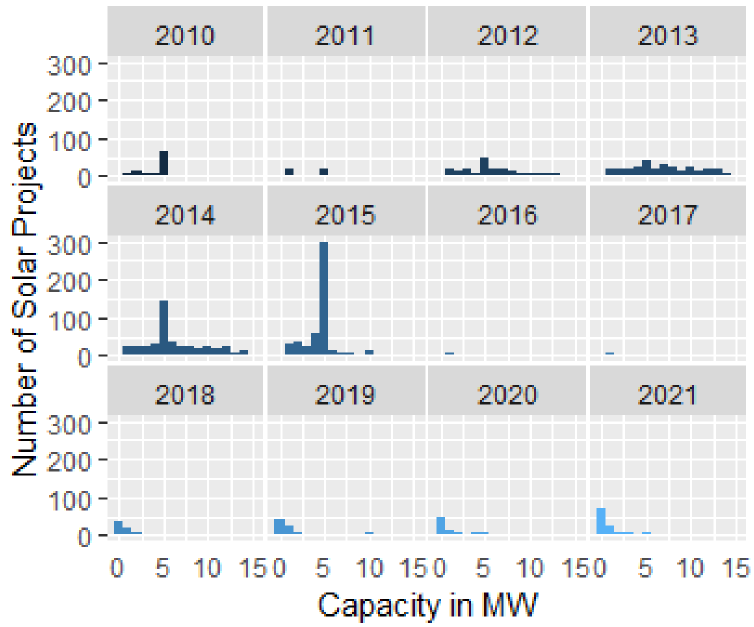

FIGURE 9. HISTOGRAM OF SOLAR PROJECTS BY YEAR

To more formally check how bunching changes over time, it is necessary to estimate the change in *relative* bunching by creating no-FiT counterfactuals for each period. I choose to estimate these in groups of years rather than individual years to avoid sample size reductions and loss of statistical power. I therefore, estimate the amount of relative bunching over three different time periods: (i) phase 1 - April 2010 to July 2012, (ii) phase 2 - August 2012 to December 2015, and (iii) phase 3 - January 2016 to December 2019. In phase 1, generators get 27 p/kWh while in phase 2, they get 9 p/kWh. Phase 3 is when the pre-accreditation process was removed and the rate fell further to 2 p/kWh.

The bunching estimates presented in Figure 10 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. In both cases, new entry is driving the vast majority of bunching.[20]

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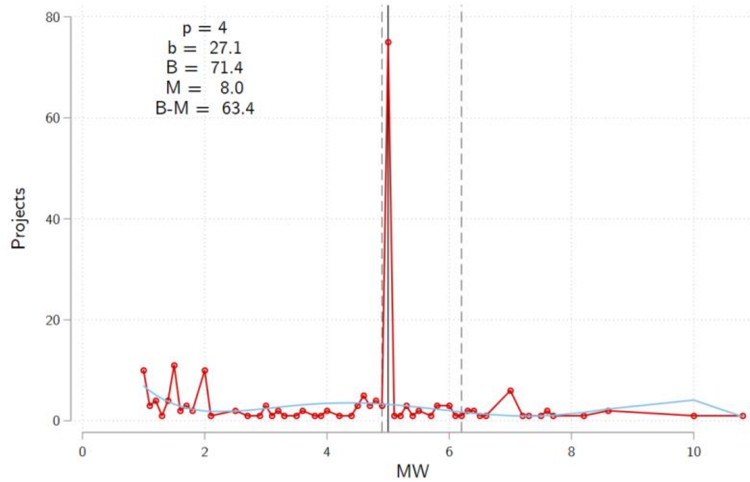

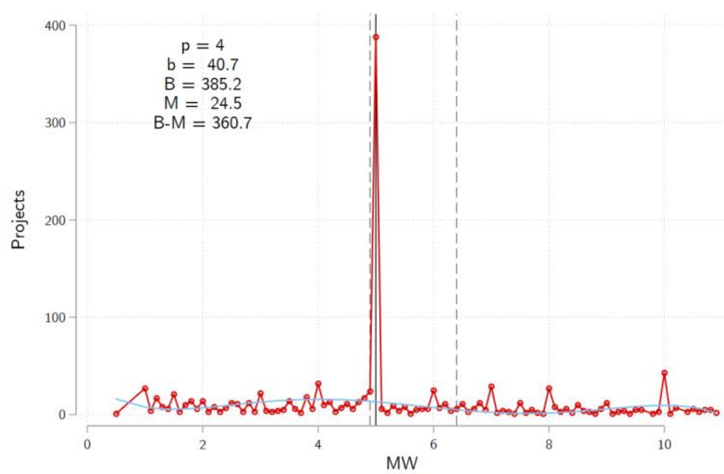

FIGURE 10: BUNCHING OVER TIME

Notes: Top: Bunching from April 2010- July 2012 , Bottom: Bunching from August 2012 - December 2015

The increase in bunching mass in phase 2 relative to phase 1 is, in the first instance, surprising since the subsidy is lower. General solar panel cost declines should not explain why the *relative* difference between the no-FiT counterfactual and with-FiT data increases. Only variables that change at the 5 MW threshold should be affecting the relative amount of bunching. However, as already discussed, a notable change between the phases was that while in phase 1, there was an option to enter with a

FiT next period, in phase 2, the imminent removal of the FiT was clear (as evidenced by public consultations) thereby increasing the value of taking it up immediately.

In a with-FiT world, firms may rationally choose to enter with a FiT tomorrow instead of today to take advantage of accumulated experience and future cost declines. However, when the prospect of FiT removal/dilution is imminent, the choice to enter with a FiT today dominates the choice of entering tomorrow without this risk hedge.

Additionally, even though the tradable certificate scheme was offering similar prices to the FiT in phase 2 (on the other side of the cut-off), the vast majority of firms still bunched at 4.9 and 5 MW, illustrating the value of a long-term risk hedges over market-based schemes that are risky due to changing prices.

Finally, in phase 3, 2016 onwards, there is no bunching, as would be expected since the scheme is highly diluted/has no guarantees for generators.

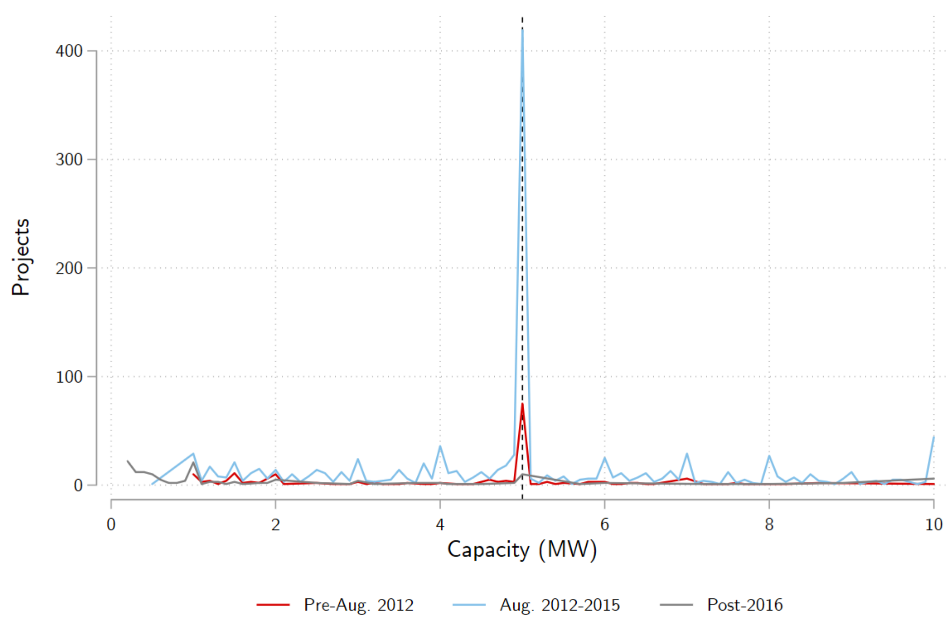

FIGURE 11. BUNCHING OVER DIFFERENT PERIODS OF TIME

Note: Counterfactuals are not shown in this plot.

Upsizing — 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.

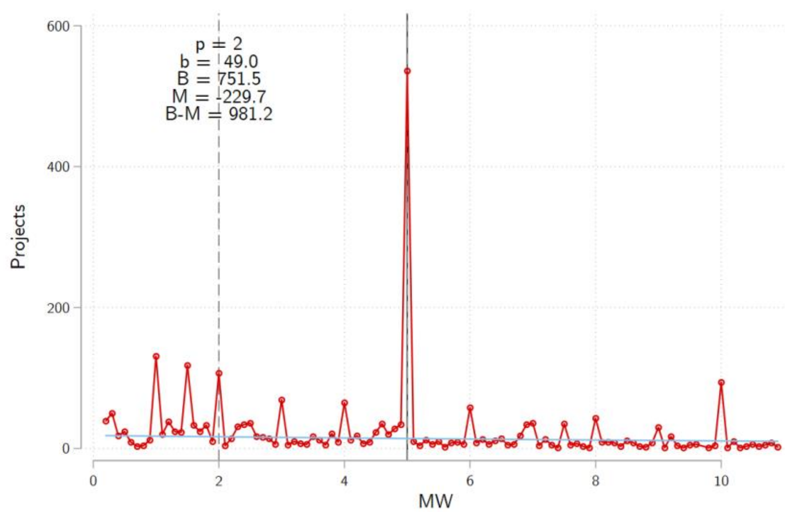

FIGURE 12 TEST FOR UPSIZING

Reference Point Effects — One cannot rule out the possibility that the FiT makes 5 MW a reference point, that is, developers decide to build farms that are 5 MW in size because it becomes salient due to the policy threshold. This has been documented in the bunching literature where agents cluster around certain values (e.g. marathon finish times, statistical results that are just under certain p-values, etc.). 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 when the 5 MW reference point is the same but other elements of the policy change. This holds constant any reference point effects. I find that firms are indeed responding strongly to changes to FiT policy characteristics as shown by the change in relative bunching mass (Section V.D).

Cheating through co-location — One may also question whether there is "cheating" whereby 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, raising suspicions that they might be cheating. I find that these projects are registered under legally separate entities. Since this is such a small share of the overall sample, the main results still hold.

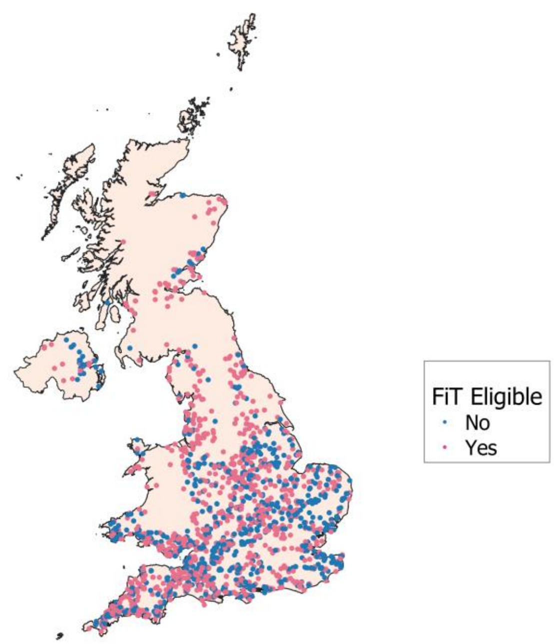

FIGURE 13: GEO-LOCATION DATA OF FIT AND NON-FIT SOLAR PROJECTS IN THE UK

Sensitivity to Order of Polynomial — Finally, Kleven (2016) 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 are recommended. Tests show that results are stable across alternative specifications.

Using a lower bound at 4.9 MW and upper bound between 6-6.5MW, I see that strategic downsizing accounts for 1-3% of the response for a third order polynomial and 3-6% of the response for a fifth order polynomial. These estimates suggest that if anything, my baseline specification is on the conservate side by presenting the larger estimate of strategic downsizing/lower estimate of new entry.

Once the upper bound is assumed to be 7 or 8 MW, for third, fourth and fifth order polynomials, the amount of strategic downsizing takes on negative values - this is the opposite of what one would expect if we believed 7-8 MW projects were downsizing to take advantage of the FiT. In other words, there is no statistically significant evidence of a “hole” up to these capacities.

VI. 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 coal-fired generation. During the growth period of solar, all other types of generation also increased except for coal, which declined. This produced climate and air quality benefits, which are weighed against the cost of subsidizing the FiT-accredited generation, which is measured in terms of the average weighted difference between the wholesale price and the fixed tariff (See Appendix D for full details related to the calculation).

I find that it takes a social cost of carbon worth £100 per tonne of CO_2 to make the FiT a net gain for society, after accounting for the health benefits of reducing SO_2 emissions/particulate matter. For comparison, 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 EU ETS (as of August 2022) are about £96.5/tCO2.

However, the government's objectives with the commercial FiT were primarily around market development rather than CO_2 reductions. Government consultations reveal how the UK was ahead of Denmark in wind power R&D in the 1980s but lost out in terms of commercialising the technology. This past experience created strong motivation to bring solar technology to market via some sort of support scheme that could eventually be phased out. Other aims included improving grid diversity, ensuring local buy-in for the energy transition, fostering innovation, and increasing local-level energy independence (DECC 2015a).

VII. Conclusion

This paper explores the role of risk reduction, via feed-in-tariffs, in bringing early-stage technologies to market, focusing on the case of utility-scale solar energy. This question is motivated by the hypothesis that due to credit market imperfections, incomplete information 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, a policy intervention that reduced the risk of investing in renewable energy projects, was effective in incentivising large amounts of entry and investment by solar generators. Since the policy's design also created incentives for strategic downsizing of projects that would have entered anyway, I also quantify the degree of such downsizing and find that it is minimal. The net effect is positive and suggests that the policy induced 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 takes a social cost of carbon worth £100/tCO2 to make the policy a net gain. Bunching by different time periods shows how even when the FiT provides a low subsidy, there is still significant bunching because firms value price volatility elimination and the prospect of the scheme being removed triggers a surge in entry. This also emphasizes the potential importance of phasing out support to counter the waiting dynamic that emerges from learning-by-doing externalities.

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 generate positive externalities and, face risks and credit market imperfections.

In terms of limitations, this work concerns itself with case of policy for nascent technologies, which occupy a small share of the market and can be modelled a price-takers. 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.

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IX. Appendix

A. Solving for the Wait Value Function

The value of waiting is given by Equation A.1

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

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

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

Note that in expectation, the choice of optimal installed capacity time across periods under a FiT is the same, that is $E_t q_{t+1}^{f*} = E_t q_{t+2}^{f*} = \cdots = E_t q_{t+T}^{f*}$. 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: $E_t V_{t+1}^{FiT} = E_t V_{t+2}^{FiT} = \cdots = E_t V_{t+T}^{FiT} \equiv \hat{V}^{FiT}$.

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

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.

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

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:

$$\text{(A.5)} \qquad \max_q V_t^w = \beta \max\{\hat{V}^{FiT}, \hat{V}^I\}$$

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

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

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, $max\{\beta\hat{V}^I, V_t^I\}$. 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.

C. Value for Money Calculations

Table 1

	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 coal displaced by solar (tCO2/MWh)	0.90	Using the carbon intensity of coal production in the UK
7	Emissions displaced by FiT Solar (tCO2/year)	1,968,635	Generation*Emissions Intensity (line 5* line 6)
8	SO2 intensity of coal production (tSO2/MWh)	0.002	Using the SO2 intensity of coal production in the UK
9	SO2 reduction from coal displaced by solar (tSO2/year)	3,991	Generation*SO2 Intensity (line 5* line 8)
10	Price of CO2 (£/tonne)	96.5	Carbon Price in EU ETS allowances (August 2022)
11	Social Cost of SO2 (£/tonne)	6,000	Social Cost of SO2, EU Commission Calculation for UK
12	Annual benefit of reduced SO2 emissions (£)	23,946,221	Line 11*Line 9
13	Annual benefit of reduced CO2 emissions (£)	189,973,258	Line 10*Line 7
14	Net subsidy given to FiT accredited solar (£/MWh)	112.0	FiT tariff - wholesale electricity price (weighted average value)
15	Annual cost of FiT solar subsidy (£)	244,985,664	Generation*Subsidy (line 5*line 10)
16	Annual benefit less cost (£)	- 31,066,185	Line 13 + Line 12 - Line 15
17	Minimum social cost of carbon to make FiT net gain	112.28	Line 15 - Line 12 / Line 7

D. Figures

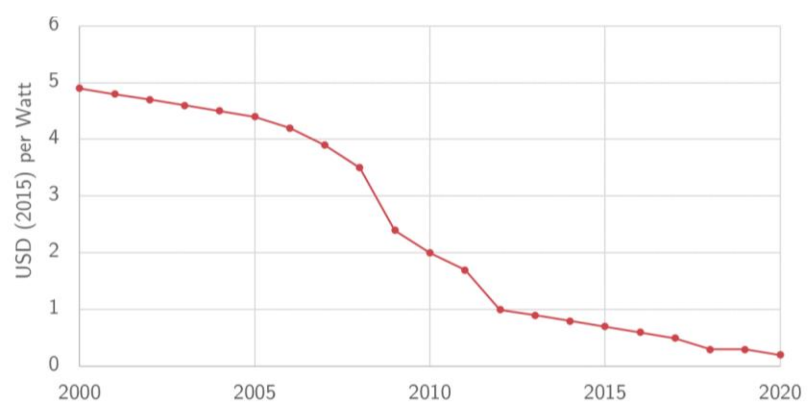

FIGURE A.1. SOLAR PANEL COSTS. SOURCE: BNEF AND NREL.