**Social equity issues in the distribution of feed-in tariff policy
benefits: a cross sectional analysis from England and Wales using
spatial census and policy data**

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Highlights

- Feed-in tariffs are subsidies involving substantial public spending commitments
- Payment distribution under the feed-in tariff in England and Wales has been substantially unequal
- Linking policy data to spatial census data can measure the degree of inequality
- Policy design that is more sensitive to participants' socioeconomic characteristics can improve distributional outcomes

Abstract

The feed-in tariff has become a popular policy instrument globally for deploying clean energy, often involving substantial public spending commitments. Yet relatively little attention has been paid to how payments made under this policy type get distributed across socioeconomic groups. This paper links information on individual domestic photovoltaic (PV) installations registered under the feed-in tariff for England and Wales, to spatially-organised census data. This makes it possible to observe which socioeconomic groups are benefitting most and least under the policy. Comparing the observed benefit distribution to a counterfactual distribution of perfect equality, a moderate to high level of inequality is found. Cross-sectional regressions suggest that settlement density, home ownership status, physical dwelling type, local information spillovers, and household social class shaped this outcome. Greater sensitivity to these factors in policy design could improve distributional outcomes under feed-in tariff policies in England and Wales, and beyond.

Keywords

Clean energy subsidies, social equity, spatial analysis, distributional impact, feed-in tariff

1. Introduction

A feed-in tariff (FiT) is a policy instrument for promoting clean energy production that works by guaranteeing a fixed payment to clean energy installations for each unit of electricity produced. Typically, it guarantees the price by contract for 10 or more years (Couture and Gagnon 2010; Madlener and Stagl 2004; NREL 2010). As of 2010, feed-in tariffs were the most popular policy approach globally for promoting clean energy deployment, with more jurisdictions using feed-in tariffs than either tax credits or renewable portfolio standards (NREL 2010; Schmalensee 2010). The United Nations Environment Program and Bloomberg New Energy Finance estimate that, as of 2010, 75 percent of all globally installed photovoltaic (PV) capacity had been deployed with the support of feed-in tariffs (UNEP/BNEF 2013).

Social equity issues are material in the context of feed-in tariff policies because these policies tend to involve very large public and private spending commitments. For example, the California Solar Energy Initiative, which facilitated deployment of mostly small-scale solar PV capacity between 2007 and 2016, had a total budget of USD 2.1 billion (CPUC 2013). The empirical subject of this paper is the feed-in tariff in England and Wales. The impact assessment carried out ahead of its launch estimated the total cumulative cost to 2030 at GBP 8.6 billion (DECC 2010).¹ By contrast, in Germany, an estimated EUR 53 billion in payments were made between 2000 and 2010 to PV installations alone under the feed-in tariff provided for by the country's Renewable Energy Sources Act (Fronzel et al 2010: 10). Given this scale of spending, more attention should be paid to social equity in the distribution of the benefits of these policies.

¹ The present research estimates the total annual cost of the program at GBP 447 million for the FiT year April 2014-March 2015 – see section 3.4. Said impact assessment estimated the annual average cost at GBP 610 million over 20 years.

This paper uses rich, comprehensive data for small statistical geographies in England and Wales to examine how the benefits of the feed-in tariff in England and Wales have been distributed across socioeconomic groups to date. The novel dataset links information about 564,074 small-scale PV installations to household socioeconomic and demographic information from the census of England and Wales, at what can be thought of as the ‘neighbourhood’ level. The combined dataset is used to measure the degree of inequality in the distribution of the benefit across socioeconomic groups and to test different explanations for this outcome that are relevant to feed-in tariff policy design.

The paper proceeds as follows: Section 2 frames the feed-in tariff, as a policy instrument, within a broader discussion about the distributional impact of taxes and subsidies in an energy and environment policy context. Section 3 discusses the empirical methods used, which involve linking policy and census information across small statistical geographies, then comparing the actual benefit distribution to a counterfactual distribution of perfect equality across socioeconomic groups. Section 4 describes the data. Section 5 presents the results and tests various hypotheses for the observed unequal outcome. Section 6 returns to the discussion of social equity in feed-in tariff design and suggests ways that such policies can be made more sensitive to equity issues, in Britain and beyond.

2. Equity issues with subsidies in energy and environment policy

Broadly speaking, policymakers attempting to decarbonise and modernise energy systems have two basic options for changing investment and consumption behaviour: taxes and/or subsidies. Questions of political feasibility aside, these options have very different distributional implications when compared in the abstract. Taxes are often designed to discourage negative externalities connected to consumption and production behaviour by

penalising the externality. Taxes on energy system pollution, however, are frequently directly *regressive* because worse-off households spend a greater proportion of income on energy goods affected by the tax, and so pay a greater proportion of income under the tax than better-off households (Advani et al 2013; Bento et al 2009). However, one advantage of taxes is that they can be augmented with policies that reduce or eliminate their first-order negative distributional incidence by returning some of the public income from the tax to poorer households (Bento 2013; Kotlikoff and Summers 1987). This is done in British Columbia, for example, where some of the revenue raised via carbon taxation is returned to worse-off households through a policy-specific, income-linked deduction on annual tax returns (Murray and Rivers 2015).

A feed-in tariff – a payment made to clean-energy producers – is, on the other hand, a subsidy. Subsidies in an energy and environment policy context do not address negative externalities but rather promote alternative modes of production or consumption that reduce or avoid those externalities. On their own, subsidies produce no revenue that could be re-distributed, so, unlike taxes, policies like feed-in tariffs cannot fund complementary social equity programmes. Insofar as the policy objective behind a feed-in tariff is to reduce pollution, a feed-in tariff is a technology-specific abatement subsidy. Abatement subsidies effectively grant polluters the right to pollute, then oblige whoever pays for the subsidy to compensate the polluters for cleaning up.² Taxes, by contrast, penalise the behaviours that result in pollution in the first place. This is one reason that abatement subsidies tend to be seen as second-best to

² Bovenberg and Goulder point out the philosophical assumption that is implicit in this: ‘In the case of an abatement subsidy, the government effectively grants pollution rights to firms, and obligates taxpayers to compensate firms for any reductions in pollution. This is consistent with the *victim pays* principle whereby the recipients of pollution must pay to induce pollution reductions’ (Bovenberg and Goulder 2001: 40).

taxes in terms of distributional outcomes (Bovenberg and Goulder 2001; Parry et al 2005; Wodon 2006).

A major political attraction of the feed-in tariff as a policy choice to date has been the argument in favour of economic efficiency. Relative to a renewable portfolio standard or other crude, quota-based deployment policy, feed-in tariffs give agents incentives to minimise the cost of a renewable energy installation while maximising production, over a long time period, given a fixed or semi-fixed compensation price. The private profit incentive that this policy design creates is likely to lead to more efficient technology, scale, location, siting, ownership, and financing outcomes than when policymakers are left to decide the technical aspects of deployment (Lyon and Yin 2010; Lesser and Su 2008; Mendonça et al 2011). Under a feed-in tariff, the agents with the best deployment opportunities should select themselves into the policy – that is, participation only occurs when the subsidy on offer compensates an agent for all investment costs (physical capital, information gathering, time, and transaction costs), after adjusting for risk and uncertainty. Unlike a tax policy, no agent should be made directly worse off by the introduction of such a subsidy, but some will be eligible to claim the allocated funding.

Consider a feed-in tariff policy where individual *households* are encouraged to participate, as in the policy analysed in this paper. It seems plausible that the efficiency-improving aspect, whereby agents are allowed to select themselves into participation, may limit participation by certain households. This might occur through multiple channels: worse-off households (that is, economically less prosperous households) may lack access to financial capital to participate in the policy at all; or they may be unable to participate to the same extent as better-off households (Feng et al 2010; Moser 2013; Parry et al 2005). Additionally, worse-off households may be less likely to know that the policy exists; they may lack financial resources, including credit, to purchase an installation (Haines et al 2007), or they may be precluded from

participation by housing tenure status such as renting (Druckman and Jackson 2008). Worse-off households may be shut out of participation because they occupy housing stocks with a limited lifespan, making a long-term investment uneconomical on its face. Finally, such households may be deterred from participation by the unpredictability of installation maintenance costs or by the technical knowledge perceived to be required to own and operate an installation (Feng et al 2010).

Recent empirical studies of the distributional impact of clean energy subsidies have produced results consistent with these hypotheses. Borenstein and Davis (2015) used tax return data from the United States to assess which households participated in tax credit programs for home weatherisation, solar panels, and hybrid and electric vehicles. They found that the bottom three quintiles of earners by income received about 10 percent of all tax credits, while the top quintile received about 60 percent. Rausch and Mowers (2014) examine the distributional impact of clean energy standards on US households. They find that these policies are regressive because they place a larger burden on regions that depend on dirty fuels (coal), and a smaller burden on (richer) regions with abundant hydropower and wind resources. Murray and Rivers (2015) show how policymakers successfully anticipated and managed distributional impact issues arising from the British Columbia carbon tax. There, tax credits for low income families were created to offset the otherwise negative incidence of the tax. Other research has sought to address these outcomes pre-emptively by providing practical guidance on fairly distributing the *cost* of feed-in tariffs (Granqvist and Grover 2016; NREL 2010).

This conceptual comparison of the differences between taxes and subsidies for social equity outcomes, plus the findings of this recent empirical work, lead to the following hypotheses about the benefit distribution of the feed-in tariff for England and Wales. The hypotheses are that (A) the benefits of the policy are being distributed across socioeconomic groups in a

substantially unequal way and (B) that this distribution is explained at least partly by factors that could be addressed through policy design that is more sensitive to equity outcomes.

3. Methods

3.1 Distributional analysis

The approach to testing these hypotheses starts with linking data from the regulatory agency administering the feed-in tariff in England and Wales to census data for those countries, on the basis of small statistical geographies. The observed distribution of policy benefit across statistical geographies is then compared to a counterfactual distribution of perfect equality. The comparison is made by using Lorenz curves, by deriving Gini coefficients from them, and by analysing the benefit distribution across socioeconomic status quintiles. A simple cross-sectional regression model is estimated to test various explanations for why some statistical geographies have secured a high level of benefit while other have not.

The following analysis only considers the distribution of the *benefits* under the policy, not the distribution of its costs. An objective of any complete distributional analysis should be to understand the distribution of policy benefits *net* of the costs of the policy borne by the same social groups. The present analysis only considers the distribution of benefits, first, because little detailed quantitative information exists in the public domain about how the cost of the policy is being distributed across households. The data that do exist are not nearly as granular or rich as the data available on policy benefits; see section 4 for details on the difficulties of obtaining cost data. The second reason is that one of the authors has dealt elsewhere, albeit in a qualitative way, with how the large new cost of clean energy infrastructure can and should be fairly spread across social groups (Granqvist and Grover 2016).

Even if the unequal benefit distribution described below were completely offset by a progressive distribution of policy costs (which it is not believed to be – see Grover 2013), there is still value in drawing attention to the benefit distribution under one feed-in tariff policy empirically, in showing how the degree of inequality can be measured in this policy context using spatial census data, and in exploring explanations for the observed distribution via regression analysis.

3.2 Policy context

The empirical context is the British feed-in tariff for small-scale clean energy installations, launched on April 1, 2010. The stated aims of the policy were to renew Britain's aging electricity infrastructure, to offset declining energy resources in the North Sea, to expand the domestic clean energy industry, and to mitigate British carbon emissions (UK DECC 2011). The policy was also seen as a way to help Britain comply with the EU Renewables Directive (2001/77/ED), which obliges it to produce 15 percent of its gross electricity consumption from renewable sources by 2020. Under the policy, British electricity suppliers are obliged to make regular payments to registered clean-energy installation owners, in proportion to the quantity of electricity produced by the installation and in line with a tariff schedule set by the energy markets regulator Ofgem. Payments are made quarterly, and all tariffs are linked to an inflation index (UK DECC 2010).

In practice, the electricity suppliers today make hundreds of millions of pounds in FiT payments to their customers each year. The policy's statutory framework provides for the electricity suppliers to recover FiT payments by passing on the cost to their customers through

an electricity bill levy (Ares 2012; DECC 2010).³ This means that the policy is paid for by electricity consumers through a utility bill levy, *not* by central government funds raised through general taxation. This raises important questions about the way the cost of the policy is distributed. These questions are beyond the scope of the present analysis, which focuses on the distribution of benefits only. However, cost-side distributive issues have been dealt with extensively elsewhere (Grover and Granqvist 2016).

Installation owners that register under the policy receive can two payment streams: a generation tariff and an export tariff. The export tariff is paid per kilowatt-hour (kWh) of electricity that is generated on site *and* fed into the grid. The level of the export tariff has been low (about £0.04 per kWh initially for a typical domestic PV installation) compared to the generation tariff (initially about £0.43 per kWh), and it has changed little over time. The generation tariff, by contrast, is paid for every kWh of electricity generated regardless of whether the electricity is used on site or fed into the grid. In this way, the generation tariff is more of a production tariff than a ‘feed-in’ tariff (Mendonça 2011). The level of the generation tariff varies by technology type, installation size, and installation owner type.

The timing of registration under the policy by installation owners has also been a very important factor in determining the level of benefit received. For almost all technologies and

³ The policy framework also provides a ‘levelisation’ mechanism designed to make sure FiT payments are distributed fairly *between electricity suppliers*. Levelisation ensures that an electricity supplier does not end up making tariff payments that are out of proportion to the market it serves because participation by its customers is exceptional (Ofgem 2010-2013). Levelisation annually transfers payments from suppliers that underpay to suppliers that overpay, so that total payments are spread in proportion to the size of the customer base served by each supplier.

size classes, the generation tariff started in April 2010 at the highest rate level and was reduced over time, sometimes through unanticipated policy announcements that substantially lowered the tariff payment (Ofgem 2012: 27-28). While this research looks at the benefit distribution across social groups almost exclusively in cross-sectional terms, it is important to say that the benefit distribution was likely influenced by registration timing factors, through the declining generation tariff. Registration timing is influential because when an installation owner registers a new installation, they lock into the tariff that is prevailing at the time of registration, for a minimum of 20 years. The authors are exploring the influence of timing and policy shocks on benefit distribution in further research.

3.3 Linking census and policy data spatially

The unit of analysis throughout the assessment of the benefit distribution is the lower layer super output area (LSOA). An LSOA is a statistical geography used in Britain for collecting census and other administrative data. It is a small spatial unit that can be thought of as a ‘neighbourhood’. The 2011 census of England and Wales divided the entirety of the two territories into 34,378 LSOAs. The mean number of households in an LSOA is 672; the mean area of an LSOA is 441 hectares (4.41 km²). The census data provide high-quality and detailed information on the aggregate characteristics of the households in each LSOA.⁴

⁴ The UK’s Office of National Statistics constructs the statistical geographies used in the census of England and Wales as follows. Clusters of adjacent postcode areas are built into output areas (OAs), the lowest geographical level at which census data are gathered. There were 181,408 OAs in the 2011 census. OAs are constructed to have similar population sizes and to be as homogenous as possible in terms of household tenure and dwelling type. LSOAs are

The census data were combined with data on individual installations that registered under the feed-in tariff in England and Wales from April 1st, 2010 (inception) to September 30th, 2015 (the most recent data available at the time of writing). The installation data contains information, for each individual installation, on installed capacity, technology type, tariff paid and the LSOA the installation is located in. On that basis it is possible to produce LSOA-level statistics by aggregating the installations within each LSOA. After matching the installation data to the census data, the analysis examines the relationships between the level of policy benefit locating in or flowing to each LSOA and the socioeconomic characteristics of the households there.⁵

Before aggregating the installation-level data to the level of the LSOA, some installations were dropped. From the full record of 666,152 installations, those registered in Scotland and the Isle of Man were dropped. This was because the authors do not have matching census data over consistent statistical geographies for these territories. This leaves installations registered

constructed from OAs in the same way. Similarly, middle layer super output areas (MSOAs) of which there were 7,161 are constructed from LSOAs in the same way.

⁵ Performing the analysis at the level of the installation and not at the level of the LSOA would have involved assigning LSOA-area characteristics to individual installations. This would have involved making untenable assumptions about the extent to which LSOA (aggregate household) characteristics reflect those of individual households. Borenstein (2012) assigns area characteristics to households using US census data, mitigating the ecological fallacy problem by using within-area distributions of household characteristics available in the US census data. However within-area distributions are not available in our data to make replication of that approach possible here.

in England and Wales. Also dropped were all installations registered at non-domestic premises (community, commercial, and industrial). Domestic installations were focused on because the household is the main social unit used to monitor social welfare and equity in England and Wales, including in the census. Also dropped were 178 installations with out-dated LSOA codes. Finally, all non-PV installations were dropped (anaerobic digestion, hydro, micro combined heat and power, wind). Only PV installations were used for consistency in calculating tariff rates and policy benefit measures. PV accounts for the majority of all registered installations (96.2 percent) and the majority of installed capacity (67.6 percent). This leaves 564,074 domestic PV installations located in England and Wales, which were then aggregated to the LSOA level.

3.4 Calculation of benefit measures

Using the installation information aggregated to the LSOA level we compute four indicators of the level of policy benefit accruing to each LSOA.

The first benefit measure, *INSTALLS*, is the count of installations in each LSOA, regardless of capacity or any other weighting information. *INSTALLS* captures benefit in a broad sense, as the number of households that have been able to participate in the policy in any capacity at all. It could be taken to signal the level of financial benefit in a crude way, but could also denote non-financial benefits such as the positive recognition households enjoy when PV ownership signals policy savvy, modernity, altruism and/or social status to households inside or outside the LSOA (Dastrup et al 2011).

The second benefit measure, *CAPACITY*, is the total installed capacity in kilowatts (kW) in each LSOA. It captures all of the benefit of *INSTALLS* and additionally how the magnitude of benefit varies due to installation size choices. This indicates the different abilities of the

households in different LSOAs to access financial or physical capital. *CAPACITY* also lets the level of benefit reflect the level of optimization in household investment choices with respect to variance in electricity consumption, available roof space, household size, and solar resource access.

The third benefit measure, *TARIFF*, is the mean of the generation tariff rates secured by the installations in each LSOA. It is measured in British pence per kWh (p/kWh). *TARIFF* is distinct from the previous two measures because it captures a payment rate under the policy independent of the frequency or capacity of installations. To ensure this independence it is calculated as a simple mean (not weighted by installed capacity for example). LSOAs with zero installations are treated as missing in calculating *TARIFF*. Higher values of *TARIFF* may reflect earlier awareness of the policy and better registration timing given that the generation tariff generally declined over time. It captures the level of benefit connected to ‘locking in’ to a tariff rate for a minimum of 20 years and the ability of households to secure more favourable registration status for their installations.

The fourth benefit measure, *PAYMENT*, incorporates information from all three preceding measures. The *PAYMENT* measure is expressed in British pounds per year. It is the estimated sum of all payments currently made per year to installation owners in each LSOA. *PAYMENT* is calculated from the installation-level information about installed capacity, tariff rate, latitude (a proxy for annual solar radiation gain), and an assumption about the amount of electricity the installation exports to the grid.⁶ The equation for calculating *PAYMENT* is given in the appendix along with descriptive statistics for the installation-level variables used to calculate it

⁶ Sensitivity analysis shown in the appendix using extreme values for the export assumption (0, 100 percent) shows no substantial difference from the results presented below.

(Tables 4 and 5). Although the installation-level figures are not used in the main analysis, the mean estimated payment per installation per year is £793.23. Once aggregated to the level of the LSOA the mean payment per LSOA per year is £13,015.28. Total payment to all domestic PV installations in all LSOAs in England and Wales is estimated at £447.4 million per year.⁷

Although LSOA boundaries are defined in part to contain similar numbers of households, three of the benefit measures can be adjusted by the number of households in each LSOA. When this is done the measures are denoted *INSTALLSHH*, *CAPACITYHH*, and *PAYMENTHH*.

3.5 Census data and socioeconomic status index

The census data include rich information on the aggregate characteristics of the households in each LSOA. This includes the percent of households by housing tenure status (renting, owning), the percent of households by dwelling type (flat, semi-detached, detached), education level, social class, employment rate, and deprivation level. The relationship between these LSOA characteristics and the benefit measures described in the previous section is explored below.

The census data do not, however, include a direct measure of either household income or wealth. This information is not collected by the census, nor by the feed-in tariff policy.

⁷ According to the British energy markets regulator Ofgem, GBP 1.1 billion in payments were made in the year from April 2015 to March 2016 (Ofgem 2016: 2). The estimate in this paper is lower because it excludes all payments made to installations in Scotland and the Isle of Man; all payments made to non-PV installations (wind, hydro, etc); and all payments to installations registered at non-domestic premises (community buildings, schools, commercial and industrial facilities).

However, the census data do contain many proxies for income and wealth and these are used to construct an index of the socioeconomic status (SES) of each LSOA. The index is likely to be correlated with income and wealth in its own right. It is also common practice in the UK to assess the distributional impact of policy across social groups defined by characteristics other than income and wealth.⁸ The SES index approach is consistent with that practice.

The SES index is comprised of four component variables: (1) the percent of households with an approximate social grade AB (*SOCIAL_AB*), (2) the percent of households owning their home outright (without a mortgage) (*OWN_OWN*), (3) the percent of economically active people unemployed (*WORK_UNEMP*), and (4) the percent of households deprived in 4 dimensions (*HH_DEP_4*). The first two are positive indicators of SES, the second two are negative indicators.

After adjusting for directionality, the variables are combined using principal component analysis (PCA). PCA creates an index score that eliminates redundancies in the index components by extracting the largest sources of uncorrelated variation across them (Jackson 2003). This method avoids problems that arise with standard additive index construction methods when, for example, the index components are correlated or share some underlying causal factor. PCA mitigates the issue of overweighting certain LSOA characteristics by extracting only the uncorrelated variation across the components.

The resulting SES variable is then used to define SES quintiles. The SES variable is ordered by its values, then four cut points are determined which divide the observations evenly into five groups of 6,875 LSOAs each. A final variable calculated is *SPILL_MSOA*. It is used to test for

⁸ See Annex 5 of 'The Green Book' (HM Treasury 2003) which provides guidelines for assessing distributional impact across groups defined by gender, ethnicity, age, geographic location, and disability.

spatial dependence in the policy benefit level in any focal LSOA that might arise from installation activity in adjacent LSOAs. This is the only variable calculated from MSOA-level information. Recall that an MSOA is the next largest statistical geography used to gather census data in the UK. An MSOA comprises about five LSOAs on average.

4. Data

Table 1 gives descriptive statistics for the variables used in the distributional analysis, including the exploratory regressions. This includes the benefit measures derived from the FiT policy component of the dataset, the socioeconomic and demographic variables taken from the census, and the SES index. The unit of analysis for all variables is the LSOA. The dataset is entirely cross-sectional.

Table 1: Descriptive statistics for variables used in distributional analysis

Variable	Description	Units	N	Mean	Min	Max	SD
<i>INSTALLS</i>	Installations	Count	34,378	16.41	0	237	17.45
<i>CAPACITY</i>	Installed capacity	kW	34,378	55.4	0	5,213.68	67.76
<i>PAYMENT</i>	Annual payment	£/year	34,378	13,015.28	0	762,780.90	15,710.01
<i>TARIFF</i>	Mean generation tariff	p/kWh	32,927	26.85	6.38	43.3	7.51
<i>HOUSEHOLDS</i>	Households	Count	34,378	674.29	304	1,405.00	132.85
<i>DENSITY</i>	People per hectare	Ratio	34,378	41.26	0.03	684.7	41.18
<i>HH_FLAT</i>	Percent households in flats	Percent	34,378	14.77	0.08	98.87	17.53
<i>SOCIAL_AB</i>	Percent households high social class	Percent	34,378	22.67	1.23	73.95	12.94
<i>OWN_OWN</i>	Percent households owning home outright (no mortgage)	Percent	34,378	31.51	0.19	77.34	13.7
<i>WORK_UNEMP</i>	Percent people economically active unemployed	Percent	34,378	4.4	0.24	20.46	2.43
<i>HH_DEP_4</i>	Percent households deprived in 4 dimensions	Percent	34,378	42.41	7.89	76.58	12.12
<i>SESINDEX</i>	Socioeconomic status index	Index scale	34,378	0	-6.04	4.88	1.71
<i>SPILL_MSOA</i>	Installations in MSOA minus installations in LSOA	Count	34,378	69.50	66.81	0	953

As discussed above, the analysis in this paper only addresses the distribution of policy benefits. The authors did try to obtain detailed data on how the cost of the policy is being distributed across social groups but did not succeed. One reason for this lack of success is that responsibility for distributing the cost of the policy falls not with the government energy markets regulator, but with British electricity suppliers, who effectively administer the policy. The authors contacted the finance departments of three British electricity suppliers (E.ON, Goodenergy and SSE) with questions about how they are distributing the policy cost across their customers. All three suppliers considered the information sensitive and proprietary and referred all questions to Ofgem.

5. Results and discussion

This section first compares the observed distribution of policy benefit against the counterfactual of a perfectly equal distribution. A substantially unequal distribution is shown. It then explores different hypotheses for why some LSOAs have done so much better under the policy than others, focusing on explanations relevant to policy design.

5.1 Main findings

The Lorenz curves in Figure 1 plot the cumulative percent of policy benefit against the corresponding cumulative percent of LSOAs. Lorenz curves are commonly used to measure within-country income or wealth inequality but they have also been used to measure distributional outcomes at policy level. See for example Borenstein and Davis (2015) and Dubin and Henson (1988), who plot energy tax credit uptake across tax payers and statistical

geographies, respectively. Lorenz curves have also been used to analyse energy and resource use, for example the within-country distribution of electricity consumption (Jacobson et al 2005) and material resource consumption (Druckman and Jackson 2008). In the curves, the diagonal line represents the perfect equality counterfactual. The curved line is the observed distribution, and the ratio between the two enclosed areas is the extent of inequality in the benefit distribution – the Gini coefficient.⁹ A higher Gini coefficient signals a more unequal distribution.

The observed distribution of policy benefit departs substantially from the counterfactual of perfect equality. The left panel of Figure 1 shows that the degree of inequality increases with the comprehensiveness of the benefit measure, although all fall in a similar range. The Gini coefficient ranges from .508 to .549 depending on the benefit measure. For comparison, the World Bank (2016) estimates the Gini coefficient for household income for the United Kingdom at .325 for 2012. This implies that the benefit of the policy is being distributed between 1.56 and 1.68 times more unequally than UK household income in general. The Gini coefficient for the policy is instead similar to the Gini coefficient for household income in Brazil in 2012 (.526).

⁹ The authors are grateful to Ben Jann (2016) for his excellent article and programming package ‘Estimating Lorenz and concentration curves in Stata’.

Figure 1: Lorenz curves

The degree of inequality can also be compared to similar policies. In the case of the UK policy, about 50 percent of the total benefit is being spread across about 85 percent of LSOAs. Borenstein and Davis (2015: 18) find for the US that 50 percent of residential energy tax credits were distributed across 86 percent of taxpayers and that 50 percent of electric vehicle tax credits were distributed across 90 percent of taxpayers. The benefit of the British policy is then distributed slightly more unequally than the US policies but is in the same general range. The right panel of Figure 1 gives the distribution of the *PAYMENT* benefit measure only, separately for England and Wales. The benefit distribution is slightly more unequal in England than in Wales. This may reflect greater underlying inequality generally in household income in England than in Wales (UK DWP 2016).

The observed and counterfactual distributions are also compared using the quintiles calculated from the SES index. In Table 2, the SES quintiles are given, and the aggregate benefit that has accumulated to, or is flowing to, the LSOAs in each SES quintile is reported. The *TARIFF* benefit measure is not used because, as a mean, it cannot be sensibly aggregated. The table shows that for the *INSTALLS* measure, 41.1 percent more installations registered in LSOAs in the fifth (best-off) quintile than in the first (worst-off). For the *CAPACITY* measure the difference is 77.3 percent and for the *PAYMENT* measure the difference is 122.5 percent. The gap increases with the information richness of the benefit measure. This remains true after adjusting for the number of households in each LSOA¹⁰ (see appendix).

Table 2: Policy benefit by SES quintile

	Q1 (worst-off)	Q2	Q3	Q4	Q5 (best-off)
<i>INSTALLS</i>	91,608	91,069	114,603	137,573	129,221
<i>CAPACITY</i>	262,865	289,358	387,503	498,556	466,102
<i>PAYMENT</i>	53,944,598	63,378,447	89,446,630	120,642,668	120,026,866

Figure 2 graphically compares this result to the counterfactual distribution of perfect equality (one fifth of the total policy benefit per quintile). The graphs show the benefit distribution across SES quintiles for each benefit measure. *TARIFF* is omitted because it cannot be sensibly aggregated into quintiles. Generally, the lower quintiles (worse-off LSOAs) benefitted less under the policy than better-off quintiles, though there are some surprises.

¹⁰ The difference in the mean per-household benefit between the first and fifth quintiles is 45.1 percent (*INSTALLSHH*), 79.3 percent (*CAPACITYHH*) and 123.8 percent (*PAYMENTHH*).

Figure 2: Actual benefit distribution compared to perfect equality counterfactual, by SES quintile

Unexpectedly, the benefit to LSOAs in the fourth quintile is higher than in the fifth quintile, for all three measures. This is true after adjusting for the number of households, as shown in the appendix. For the *PAYMENT* measure which incorporates the most comprehensive benefit information, the difference narrows but does not disappear.

One explanation for this unexpected finding may lie in settlement density. Greater settlement density may have held back policy participation at the best-off end of the distribution in two ways. First, the best-off LSOAs may have been located in and around cities and so also faced strong space constraints. Space constraints reduce the amount of solar radiation gain available per square meter of land. Participation may have made less financial sense for households with smaller space endowments. Second, if the very best-off LSOAs were also denser, then one might also expect more households residing in apartment buildings. From the

point of view of erecting solar PV this could present legal impediments to accessing roof space that may be physically available, but held in common ownership. These explanation are explored further below.

5.2 Explaining the distribution

Before presenting the regression results we explore in a visual way several bivariate relationships between benefit level and the socioeconomic characteristics of LSOAs. Figure 3 below presents the distribution of two benefits, *TARIFF* and *CAPACITY*, against two census variables: the proportion of households in social class AB (*SOCIAL_AB*) and the proportion of households living in flats (*HH_FLAT*). Confidence intervals are shown at the 95 percent level. In the left panel, the grey distribution is a histogram of the LSOAs for *SOCIAL_AB*. It shows that in the bulk of LSOAs, between 5 and 30 percent of households are classified as social class AB. Overlaid are the means of *CAPACITY* and *TARIFF* for the LSOAs in each percentile of the distribution. The units of these measures are kW and British pence respectively, and as the scales are similar, are read against the same y-axis. In the right panel of Figure 3, the x-axis census variable is the proportion of households living in flats instead.

Figure 3: Variation in benefit measures by socioeconomic characteristic

In the left panel of Figure 3 the mean of *TARIFF* is shown to increase positively and mostly linearly with the mean of *SOCIAL_AB*, indicating that better-off LSOAs managed to capture higher tariff rates. This sharply contrasts with the mean of *CAPACITY* whose relationship to *SOCIAL_AB* takes an inverted-U shape. This is interesting because it means that the highest social status LSOAs achieved the highest average tariff rates, even though the gross financial benefit they received may have been more limited. Put another way, better-off LSOAs did consistently better *per unit* of installed capacity, even if they installed less capacity. This suggests that households in these LSOAs were effective at timing their registration under the policy to capture the highest tariff rates.

The right panel of Figure 3 shows the relationship between the same two benefit measures and the structural characteristics of households' dwellings. There, the mean of *CAPACITY* declines continuously with the percent of households residing in flats. This is likely due to lower solar radiation gain per household per square meter in those LSOAs as discussed above, and the problems with accessing common roof space that come with flat living. Again there is

a sharp contrast with the mean of *TARIFF*, which is flat or rising with the proportion of households in flats. This implies that even though LSOAs with a high proportion of flats may have been constrained in the amount of capacity they could install, they still managed to achieve the same tariff rates on average – or even better tariff rates on average beyond about the 80th percentile.

Taking the settlement density explanation a step further, Figure 4 spatially explores the relationship between benefit level and density. Mapping *PAYMENTHH* shows that the urban areas of London, Birmingham, Manchester and Cardiff received the lowest payment level per household (the units of the legend). Less densely settled areas in mid Wales, southwest England, the East Midlands, and Yorkshire received the highest.

Figure 4: Policy payment per household (£s)

Note: each band contains one-fifth of the LSOAs.

A regression framework is used to test the hypotheses for why some LSOAs benefitted more from the policy than others. The data are fitted to a simple additive model where the dependent variable is, in turn, each of the four benefit measures (*INSTALLS* is used indicatively below). The regressions are exploratory in nature. The regressions are cross-sectional at LSOA level i consistent with the data structure. Estimation is by OLS. Errors are clustered on MSOAs (see footnote 4) j , meaning they are assumed independent across clusters but correlated within them. This and the local information spillover variable address spatial dependence to an extent (see Allan and McIntyre (2017) for a thorough treatment of spatial dependence issues in a similar context). All variables are in linear form.

$$\begin{aligned} \text{INSTALLS}_i = & \mu + \beta_1 \text{DENSITY}_i + \beta_2 \text{HH_FLAT}_i + \beta_3 \text{OWN_OWN}_i + \beta_4 \text{EMPLOYMENT}_i \\ & + \beta_5 \text{SOCIAL_AB}_i + \beta_6 \text{SPILL_MSOA}_i + \beta_7 \text{HOUSEHOLDS}_i + \varepsilon_{ij} \end{aligned}$$

Controlling for the number of households in the LSOA, six hypotheses are tested. The first is that policy benefit was lower in LSOAs with fewer square meters of solar radiation gain per person. This is tested with the variable *DENSITY*, the number of people per hectare. Second is that policy benefit was lower in LSOAs where households faced greater access restrictions to common property space (roofs for example). This is tested with the variable *HH_FLAT*, the percent of households living in flats. Third is that policy benefit was greater where households had greater pre-existing wealth to purchase a PV installation outright. This is tested by *OWN_ - OWN*, the percent of households owning their home outright. Fourth is that policy benefit was greater where households had a regular source of income they could use to pay off a loan to purchase a PV installation. This is tested with *EMPLOYMENT*, the percent of economically active households unemployed (the inverse of *WORK_UNEMP*). Fifth is that policy benefit was greater where households were more able to calculate the returns to participation, and to optimise investment levels and registration timing. This is tested with *SOCIAL_AB*, the percent

of households of high social status. Sixth is that an LSOA with neighbouring that participated more in the policy, itself benefitted more under the policy. The expected mechanism is information about registration timing and installation sizing that spills over from the non-focal LSOAs in the MSOA to the focal LSOA. This hypothesis is tested with the variable *SPILL_MSOA*. The results are given in Table 3.

Table 3: Regression estimates

	(1) <i>INSTALLS</i>	(2) <i>CAPACITY</i>	(3) <i>TARIFF</i>	(4) <i>PAYMENT</i>
<i>DENSITY</i>	-0.0609*** [0.006]	-0.261*** [0.022]	-0.00100 [0.002]	-63.36*** [5.185]
<i>HH_FLAT</i>	-0.119*** [0.011]	-0.367*** [0.043]	0.0522*** [0.005]	-78.44*** [10.351]
<i>OWN_OWN</i>	0.144*** [0.015]	0.605*** [0.055]	0.0177*** [0.005]	170.7*** [13.183]
<i>EMPLOYMENT</i>	0.159 [0.119]	1.386*** [0.352]	0.338*** [0.037]	314.5*** [83.430]
<i>SOCIAL_AB</i>	-0.0469*** [0.013]	-0.0847* [0.044]	0.174*** [0.005]	37.53*** [11.088]
<i>SPILL_MSOA</i>	0.111*** [0.011]	0.355*** [0.033]	0.00473*** [0.001]	83.05*** [7.577]
<i>HOUSEHOLDS</i>	0.0191*** [0.001]	0.0742*** [0.004]	0.00133*** [0.000]	18.75*** [0.941]
Constant	-18.55* [10.549]	-152.8*** [31.049]	-11.89*** [3.398]	-37923.7*** [7373.158]
Mean of DV	16.40	55.39	26.86	13,015.28
R2	0.367	0.313	0.153	0.347
F-stat	516.710	393.688	506.941	444.701
N	34378	34378	32927	34378

b/[se]. Robust standard errors clustered on MSOAs. * p < 0.10, ** p < 0.05, *** p < 0.01

The main interest is in the magnitude and direction of the test variable coefficients across specifications, and in the comparative magnitude of the coefficients within specifications. All estimates should be considered correlational only. In Table 3, *DENSITY* holds a negative relationship with all four benefit measures as expected, holding everything else constant, consistent with the idea that LSOAs with greater settlement density are benefitting less under the policy. *HH_FLAT* holds a negative relationship with all of the benefit measures except for

TARIFF, where the relationship is positive. This exception supports the idea that some LSOAs benefitted a great deal in terms of the rate of benefit (pence per kWh produced) but substantially less in terms of the gross benefit level (when adjusted by installation count or installed capacity). *OWN_OWN* has a positive relationship with all four benefit measures consistent with the hypothesis that greater pre-existing wealth facilitated the acquisition of PV installations and in turn increased the policy benefit level. *EMPLOYMENT* also performs consistently with the hypothesis that more regular household income facilitates installation acquisition and policy participation.

SOCIAL_AB, by contrast, associates negatively with two of the benefit measures, which would imply that higher social-status LSOAs benefitted less under the policy. This could be because high social-status LSOAs had better alternative uses for their time and financial capital. However the estimates imply that higher social-status LSOAs did better in terms of capturing higher tariff rates and securing greater overall payments as shown the positive relationship with the *TARIFF* and *PAYMENT* measures. Finally, the positive coefficient on *SPILL_MSOA* supports the information spillover hypothesis: the benefit level was greater in LSOAs that had neighbours that participated more in the policy.

The magnitude of the test variable coefficients can also be compared within specifications. *PAYMENT* is the most comprehensive benefit measure. Comparing coefficients within the *PAYMENT* specification is facilitated by the fact that all test variables are measured as the percent of households (or people) in the LSOA possessing the characteristic. The estimates indicate therefore that a one-unit (one percentage point) increase in settlement density (*DENSITY*) associates with £94.86 less estimated payment to the LSOA annually, on average, holding all else constant. The same increase in the proportion of households in an LSOA residing in flats (*HH_FLAT*) associates with £102.5 less estimated payment to the LSOA. On the whole the regressions suggest that the underlying physical, financial and social

characteristics of the households in LSOAs can be strong predictors of the policy benefit level that accumulates to LSOAs. These estimated relationships should be useful for policymakers wishing to design feed-in tariff policies in ways that counteract these drivers and the unequal benefit distribution that they seem to facilitate.

6. Conclusions and policy implications

We motivated this discussion of social equity issues in feed-in tariff design by the fact that feed-in tariffs have become one of the most popular policy instruments globally for deploying clean energy. We set out our concern that not enough attention is being given to social equity issues in policy design, given the scale of public and private funds flowing into feed-in tariffs. We demonstrated that the substantially unequal distribution of benefit arising under the British feed-in tariff policy starts not with the design of the policy itself, but with the choice to use subsidy-based policy instruments to modernise and clean up energy systems, as opposed to taxes. We acknowledged that feed-in tariffs leverage return-maximising behaviour of agents and so are likely to deploy clean energy capacity more efficiently than some policy alternatives. But we also showed how relying too heavily on this behaviour can exclude certain agents from participating in the policy at all, potentially resulting in worse distributional outcomes.

This expectation was largely substantiated in our analysis of the distribution of domestic PV installations, and payments to them, under the feed-in tariff in England and Wales. One of our methodological contributions in doing so was finding a way to measure, on the basis of small statistical geographies, the policy benefit distribution across socioeconomic groups, by linking policy information with census data. It seems to us that this approach could be easily replicated in policy jurisdictions that collect spatially disaggregated data on aggregate household characteristics, and that it could be used to evaluate equity outcomes at regular

intervals while a feed-in tariff policy is active. This spatial approach fits well with geography-based system of political representation used in many jurisdictions, where elected representatives advocate on behalf of their constituents. Monitoring equity through the spatial distribution of policy benefit could allow representatives to respond to and correct unfavourable distributional outcomes more quickly than if the benefit distribution were being measured aspatially on the basis of incomes alone.

We also recognise that while our statistical geographies approach gives near-perfect spatial coverage and leverages high quality census data, it also aggregates individual households in ways that may obscure important distributional outcomes within LSOAs. At least in the British case, a more granular analysis would certainly be possible using even more disaggregated census data (OAs) or by estimating household-level characteristics from area-level characteristics (Borenstein 2012). The pragmatic solution for policymakers however may be to collect income (evidence of household income) or wealth (home ownership status) information from participating agents when they register under the policy, so that the benefit distribution can be monitored concurrently with the fulfilment of the policy's main objectives.

A broader caveat to our research relates to the distribution of feed-in tariff policy *costs*. As we have tried to emphasise throughout, we have considered only the distribution of policy *benefits* in our analysis and not the distribution of policy *costs* (though one of us has dealt extensively with the cost distribution issue elsewhere, albeit in a qualitative way that avoided the need for microdata [Grover and Granqvist 2016]). Another pragmatic approach for policymakers to address an unequal benefit distribution is simply to adjust how the policy cost is distributed. This can be done by asking better-off households to contribute more to the policy through an electricity bill levy that is proportionate to consumption or household income. The point is that the *net* benefit distribution is what truly matters from a social equity point of view. Unfortunately, understanding the net benefit distribution of the British policy requires much

more detailed quantitative information on the cost distribution side than we were able to obtain. For policymakers, systematically collecting cost distribution information would be an effective way to measure and monitor the net benefit distribution.

A feed-in tariff policy is often one of a range of policies used to correct socially undesirable outcomes produced by energy systems left to operate on their own. In Britain, for example, various other policies and programs exist specifically to assist low-income and vulnerable groups with the cost of electricity and fuel (Advani et al 2013). To the extent that better-off households are benefitting more under the feed-in tariff, worse-off households are almost certainly benefitting more under these other policies. Policymakers should certainly consider the extent to which equity issues in feed-in tariff design are offset by policies which disproportionately benefit worse-off households. However, we take the view that the existence of such policies should not justify the creation of new negative impacts on social equity, especially when the impacts are inadvertent.

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Appendix

Equation 1: Annual payment per installation

$$PAYPA_i = (CAPKW_i * KWHPA_l * GENTAR_t) + ([CAPKW_i * KWHPA_l * .25] * EXPTAR_t)$$

PAYPA is the estimated annual payment to installation *i*. *CAPKW* is the installation's registered capacity in kW. *KWHPA* is the number of kWh that a kW of installed capacity would be expected to generate given the solar radiation gain at the installation's latitude. This is determined at LSOA-level (*l*) by matching the latitude of the LSOA where the installation is registered to PV generation performance data.¹¹ *GENTAR* and *EXPTAR* are the generation and export tariffs that were prevailing at the time the installation registered. They vary at tariff-level, *t*. Again, payments from the export tariff and the generation tariff are additive: both tariffs are paid to a kWh that gets exported to the grid. Descriptive statistics are given below for the variables used to calculate Equation 1.

¹¹ Expected PV performance data by latitude comes from the European Commission Joint Research Centre, Institute for Environment and Sustainability, Renewable Energies Unit: <http://re.jrc.ec.europa.eu/pvgis/apps4/pvest.php>.

Table 4: Descriptive statistics for variables used to calculate installation payment

	Units	N	Mean	Min	Max	SD
<i>PAYPA</i>	£	564,074	793.23	1.26	226,839.70	895.66
<i>CAPKW</i>	kW	564,074	3.38	0.02	3,150.00	5.71
<i>KWHPA</i>	kWh	564,074	897.19	788	975	38.55
<i>GENTAR</i>	£	564,074	0.28	0.06	0.43	0.14
<i>EXPTAR</i>	£	564,074	0.04	0.03	0.05	0.01

Table 5: Benefit distribution by quintile, household-adjusted

	Perfect equality	Q1 worst-off	Q2	Q3	Q4	Q5 best-off
<i>INSTALLSHH</i>	0.025	0.020	0.020	0.025	0.030	0.029
<i>CAPACITYHH</i>	0.087	0.058	0.063	0.084	0.108	0.104
<i>PAYMENTHH</i>	21.10	11.950	13.760	19.380	26.010	26.740