Social equity and technology diffusion:
Evidence from the British feed-in tariff for small-scale PV systems

Working paper, not for external circulation

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Abstract

We investigate the idea that widening levels of within-country income inequality may be linked to the increasing pace of technological change and particularly the characteristic pattern by which new technologies diffuse across social groups. We investigate this social equity-technology diffusion relationship empirically in the context of the British Feed-in Tariff (FiT) for small-scale renewable energy installations, a clean energy policy that pays out around £500 million each year in clean energy subsidies. We examine how the costs and benefits of the program have been distributed across rich and poor households during the scheme's first three years of operation. We match data for around 360,000 PV installations to socio-economic data from the 2011 census of England and Wales. We regress the financial returns to PV uptake to each adopting household on the socio-economic characteristics of the areas where installations are located. In terms of policy implications we find that a disproportionately small number of installations have located in relatively poor areas and a disproportionately large number of installations have located in relatively rich areas. Skill biased technological change has been the main hypothesis connecting technology to rising levels of social inequality. Our research advances and tests a new hypothesis: that the pattern in the way new technology diffuses across social groups reinforces preexisting levels of inequality.

JEL codes: O33, O38, Q42, Q48, Q55, Q58

Key words: social equity, technology diffusion, energy, public finance

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Acknowledgements

The authors gratefully acknowledge the support of the Centre for Climate Change Economics and Policy (CCCEP) and the Grantham Research Institute on Climate Change and the Environment. CCCEP was established in 2008 to advance public and private action on climate change through rigorous, innovative research. The Centre is hosted jointly by the University of Leeds and the London School of Economics and Political Science. It is funded by the UK Economic and Social Research Council and Munich Re. More information about the Centre for Climate Change Economics and Policy can be found at: http://www.cccep.ac.uk.

The Grantham Research Institute on Climate Change and the Environment was established in 2008 at the London School of Economics and Political Science. The Institute brings together international expertise on economics, as well as finance, geography, the environment, international development and political economy to establish a world-leading centre for policy-relevant research, teaching and training in climate change and the environment. It is funded by the Grantham Foundation for the Protection of the Environment, which also funds the Grantham Institute for Climate Change at Imperial College London. More information about the Grantham Research Institute can be found at: http://www.lse.ac.uk/grantham/

The authors also wish to thank the Institute for Fiscal Studies and three external reviewers for their critical and informed comment.

1. Overview

The United Kingdom (UK) is investing billions of pounds per year in new clean energy infrastructure. According to the Office of National Statistics, UK electricity sector investment was the highest on record in 2012, at £12 billion, up from an average of £5 billion between 2005 and 2009. Clean energy infrastructure investment is part of a sweeping program of electricity market reforms in the UK which the government estimates will require £100 billion of additional investment between 2014 and 2020 to implement (DECC 2014). While policymakers and the broader debate are attentive to questions of economic efficiency in how the UK goes about 'decarbonisation', arguably less attention is being paid to social equity issues in the way the cost of decarbonsiation is being spread across rich and poor households.

Our first aim in this paper is to examine the distributional incidence of a major British clean energy infrastructure policy, the British feed-in tariff (FiT) for small scale photovoltaic (PV) installations. Thanks to attractive government subsidies, over 360,000 households in England and Wales have chosen to erect PV installations at their properties under the policy, amounting to a 2 percent expansion in total UK electric generation capacity in three years. These households in aggregate are now receiving over £500 million per year in subsidies for the clean energy they produce, and will continue to receive this level of subsidy for at least 20 years. Our analysis shows that a disproportionately large share of these subsidies is flowing to better-off households. This is because better-off households erected PV installations sooner, captured the most favorable financial incentives under the policy by signing up sooner, and by erecting larger PV systems. Balancing the distribution of the benefits of the program against available information on the distribution of its costs, we estimate that the policy is transferring £XX million per year from the lower half of the income distribution to the upper half.

Our second aim is to use the evidence from the widespread uptake of PV across England and Wales to investigate a hypothesis about the relationship between rising levels of income inequality in the UK and the emergence and uptake of new technologies more generally. The main way that technology has been implicated in rising income inequality to date is through skill-biased technical change (SBTC), which posits that new technologies augment the productive capacity of high skill workers but not low skill workers, causing high skill worker wages to pull away because they are in relatively scarce supply. We propose a complementary explanation for the relationship between technology and inequality rooted in the outsized welfare gains adopting a new technology confers on early adopters in particular. We explore this hypothesis by combining data on the timing of household PV adoption with 2011 UK census data on households' socioeconomic characteristics.

While the impact of PV technology itself on inequality in Britain is of course likely to be small, it allows us to test the idea that successive and increasingly frequent 'waves' of new technology could compounding pre-existing inequalities through the patterns by which they diffuse across social groups over time.

Section 2 combines insights from the SBTC and technology diffusion literatures into a framework for elaborating the relationship between social inequality, the emergence of new technologies, and the socio-temporal patterns by which they diffuse. Section 3 describes the policy framework behind the British feed-in tariff and the data we use to test our hypothesis. Section 4 estimates the financial return on PV capital invested by the households that participated in the program, as a function of the socioeconomic characteristics of households, as well as how the elasticity of this relationship changed throughout the program over time. Section 5 elaborates our contribution to the understanding of the role of technology diffusion patterns in how social equity is produced and reproduced.

2. Inequality, technology, diffusion

Within-country income inequality has been on the rise in the UK and the US since the 1970s, and this trend appears to have taken hold in other OECD countries since the early 1990s (Acemoglu and Autor 2011; Atkinson et al 2011; OECD 2008). Among the many explanations for rising income inequality is technology. Skill biased technological change is the main hypothesis implicating technology in rising levels of social inequality. The hypothesis posits that the accelerating rate of technical change, particularly in information and communication technologies (ICT), complements the skills sets of high skill workers but substitutes for the skill sets of low skill workers. Architects who once drafted blueprints by hand now benefit from computer hardware and software in terms of output and quality, as do financial services and medical professionals. Technological progress has not benefitted low skill workers whose skill sets are not complementary; indeed these workers tasks are in some cases being performed by robots. SBTC posits that labour markets therefore reward the skill sets that exploit the productivity benefits made possible by new technologies, leading to wage rises for high skill workers as demand outpaces supply (Galor and Moav 2000; Jaumotte et al 2013; van Reenan 2011). A technology shock has upset the supply-demand balance.

There are at least two reasons for thinking that the SBTC hypothesis may not be capturing the whole story about the role of technology in rising social inequality. The first is that it is a complicated hypothesis to test empirically, requiring microdata on individual workers' technology adopting timing and their subsequent wage changes, within a broader labour market environment upon which many other forces are acting, including over time. The second is that wage income is a large part of total income but it is not everything: households have substantial non-wage income especially where wealthier households have capital gains and older households may be draw on a pension or savings. The SBTC explanation is therefore constrained to explaining diverging wage income when in fact the inequality-generating effects of new technology may also relate to non-employment income.

New technology takes root within a population and if successful spreads across the population in line with some broad patterns. For firms, industries and countries, adopting a new technology is usually associated with productivity gains, either because the technology itself confers an instrumental advantage that the adopter can exploit in competition with other agents, or because the adopter already possessed the skill and capital endowment needed to reap the benefit of the technology, which in turn inclines it to adopt new technology in the first place (Hall and Kahn 2003; Stoneman 1980). Households adopt new technology too, except in their case the 'productivity' benefit takes the form of higher disposable income and improvements in other aspects of general well-being, such as personal health outcomes and time spent in leisure, which may not have an immediate market value. However there is no guarantee that adopting a new technology will improve a household's or any other agent's position, given that adoption also entails risk (Dercon and Christiansen 2007; Koundouri et al 2003; Stoneman 1980). It is not unreasonable to expect that for some households the cost of learning to use a new technology in terms of time and effort is so high that the would-be benefits of adoption, however large, are outweighed by the costs.

Several aspects of the diffusion process are consistent with our hypothesis that the net welfare (income) gains to the emergence of new technologies come to be spread unequally across population subgroups by and through the diffusion pattern itself, first, and second, that this unequal distribution of new wealth reinforces pre-existing unequal welfare levels across social groups (households) that existed prior to the shock.

Following Stoneman and Battisti (2010) any single household would be expected to adopt a given technology if

$$v_{t0...k} > \rho_{t0..k}(r+\delta)+\kappa_{t0..k}$$

where the net benefit of adoption v is greater than the capital cost of adoption ρ, multiplied by the interest rate r plus the capital depreciation rate δ, plus any additional new cost involved in adoption relative to a non-adoption baseline, such as time spent learning.

To make this concrete one can think of v as the amount of new disposable income the household expects to realize over the full lifetime of the investment, where that new income is discounted back to the present day. While the interest rate and discount rate are assumed to be fixed with respect to time, the cost of learning for a household varies over time. A household that is unwilling to adopt in period $t = 0$ may observe its neighbor adopting in a subsequent period, and choose to adopt sooner than it would have on the basis of the information transmitted by the neighbour's decision ('peer effects' as in Bollinger and Gillingham (2012) but Mansfield (1968, 1989) originally on the role of information in epidemic diffusion theories).

The big observable cost of adoption is the cost of the capital good ρ which the new technology is often embodied in. The capital cost of adoption varies with time and the timing of adoption is linked to the cost of capital. The cost of adoption tends to decline with the number of adopters due to economies of scale in manufacturing, learning-by-doing by manufacturers, and social learning by would-be adopters (Arrow 1962, Linderman and Soderholm 2007). Capital cost declines are also consistent with the well-documented learning-curves in manufacturing where the unit cost of production declines with the cumulative number of units produced (Dutton and Thomas 1984; Karshenas and Stoneman 1993). At the same time the value of adopting new technology changes over time, not least for network technologies (telephone) with the number of other adopters (Reinganum 1981). Reinganum's for example found that sequenced adoptions can result entirely from strategic behavior among firms rather than from information imperfections or other differences across firms. In this view, differences in diffusion rates across industries or across technologies reduce to comparing incremental benefits (Quirmbach 1986). All this means that the net return to adoption v also varies by time (Hall 2004).

Different social groups within a population are likely to expect different net benefits with respect to the adoption decision. Groups of households may be distinguished on the basis of education level for example, and superscript $q(x)$ now denotes household education quintile. Net expected income from adoption is still expected to vary over time but the expectation is that, given the average adoption moment of all possible adoption moments $t \ldots k$, first-quintile education households face smaller expected returns than fifth-quintile education households:

$$v_{t0...k}^{q(1)} < v_{t0...k}^{q(5)}$$

We are not aware of a study that examines the specific relationship between expected household income from technology adoption and household education level (or socioeconomic status) without early adoption, though several empirical papers touch on aspects of this problem. In terms of comparable adoption studies at the household level, Muller and Rodes (2013) tested the effect of socioeconomic status on the propensity to adopt PV technology in the town of Wiesbaden, Germany between 2000 and 2009. They found that early adopters were of higher socioeconomic status where SES was measured by annual buying power. Dastrup et al (2011) estimate the capitalization value of PV installations into home prices in California. They find that the capitalization premium is larger in communities with a greater share of college graduates. They suggest that the 'observability' of a PV installation confers a kind of 'green' social status on its owner. Korda, Clements and Dixon (2011) investigated the relationship between socioeconomic status and the diffusion of coronary procedures in people with ischaemic heart disease in a large sample of Australian hospital and mortality data. They found socioeconomic lags in diffusion of two such procedures with adoption rates peaking earlier in higher SES patients. Abdulai and Hoffman (2005) modeled the long term adoption rate of crossbred cows among farming households in Tanzania. They found that the greater the schooling of the household head, the sooner adoption occurred, what they attribute to a superior ability of educated farmers to recognize the benefits and costs of the new technology sooner. In a study of mobile phone diffusion across Chinese regions during 1989-2004, Ding et al (2010) found that regions with better socioeconomic conditions adopted mobile telecommunications earlier. Ding et al (2011) analysed the income inequality impact of a government program to increase agricultural incomes in rural China through adoption of a combination of hybrid rice varieties, terracing and/or chemical fertilizer. They found that farmers who adopted these technologies had incomes that were approximately 15 percent higher than non-adopters but that the impact on income inequality was relatively small. This was because lower-income farmers adopted the technology at rates that were roughly equivalent to those of higher income farmers.

Our hypothesis therefore is that some part of rising welfare inequality (not just income inequality) in the UK is explained by the pattern through which new productivity- and welfare-enhancing technologies take root and spread throughout a population of individuals or households. The timing of uptake creates both new inequalities in the distribution of the technology's productivity benefits – 'new wealth' – and also compounds existing inequalities, since the best-off individuals are more likely to capture the highest returns to new technology. The mechanisms is the timing of adoption: better-off households are better able to assess the net benefit of adoption and they are able to do this sooner, allowing them to seize outsized adoption returns when they observe them.

3. Empirical application: the British Feed-in Tariff

Because widespread PV installation uptake occurred under a policy framework that heavily influenced the parameters of the return to an investment in PV, we are able to do more than estimate the relationship between adoption timing and social status, a relationship that frequently shows that better-off households adopt earlier. We are able to calculate actual expected returns to the PV capital investments made by households for the total investment lifetime of 20 or 25 years, and to estimate *how much greater* the return on investment was for better-off households relative to less well off ones. This is possible because the policy structure under which uptake occurred largely determined the income parameters. From calculating *how much more* financial gain accrued to rich households than poor households, we are able to calculate the aggregate benefit of the *arrival* of the new technology possibility to different income groups.

When adoption timing is unmasked and shown to flow from investment fundamental, the interest shifts from the timing of the adoption event conditional on adopter characteristics, to the magnitude of lifetime return the adopter secures through timing the investment by balancing cost and benefit trends (which vary over time).

In autumn 2008 the UK government announced its intention to introduce a feed-in tariff (FiT) to encourage uptake of small scale renewable and low-carbon energy generation systems across England, Scotland and Wales. The policy was partly motivated by the EU Directive on Electricity Production from Renewable Energy Sources (2001/77/ED) under which the UK had a target to produce 10 per cent of its gross electricity consumption from renewable energy sources by 2010, and continues to have a 15 percent target for 2020 (DECC 2011). Other motivators were to renew an aging electricity infrastructure, stimulate growth in the microgeneration sector during recession, and address energy security and dependence concerns connected to the depletion of domestic oil and gas reserves. The FiT scheme opened to registrations on April 1st, 2010. [1]

Under the FiT scheme, owners of small scale renewable energy installations receive payments from their electricity supplier for the electricity they produce. They are paid for each

[1] The scheme is open to any household, community organisation, business, farm, or other establishment with an eligible small scale renewable energy installation. Qualifying technologies include solar photovoltaic (PV), wind turbines, hydroelectric, anaerobic digestion and micro-combined heat and power (micro CHP). The maximum size of an eligible installation is 5 megawatts (MW).

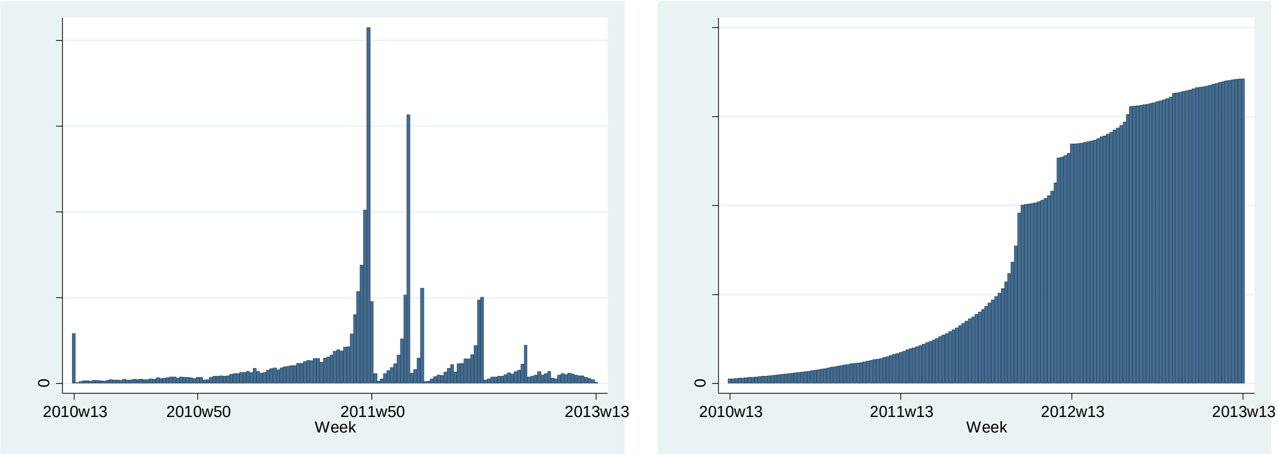
kilowatt hour (kWh) of electricity in line with a tariff schedule set out by the energy markets regulator, Ofgem. The tariff varies by technology type, installation size and owner type (domestic, community, commercial, industrial). FiT payments are index-linked and therefore inflation-proof, guaranteed by the government for at least 20 years, and paid regularly to the installation owner by the electricity supplier via bank transfer or cheque.

Installation owners can benefit from two separate streams of tariff payments and most do. Under the ‘generation tariff’ the installation owner is paid for each kilowatt-hour (kWh) of electricity generated regardless of what is done with the electricity. The tariff paid to a typical domestic PV installation at the beginning of the program was around 40p per kWh. This was down to around 12p by March 2013. Separately, under the ‘export tariff’ the installation owner is paid per kWh of electricity exported to the grid in excess of that consumed on site. The export tariff at the time of writing is about 4.5p. Given that the generation tariff is considerably larger than the export tariff, installation owners have stronger incentives to produce electricity for personal consumption rather than export. The FiT scheme therefore resembles something closer to a ‘production’ tariff than a ‘feed-in’ (to the grid, or export) tariff (Mendonca 2011, Ofgem 2011, Ofgem 2012).

The level of household participation has been rather spectacular in with 379,000 installation owners registering in the three years from April 1st, 2010. Total registered generation capacity was 1,792 MW, equivalent to about three medium-sized coal-fired power plants and accounting for around 2 percent of all generating capacity in the UK.[2] Approximately one in every 50 households in England and Wales now has an installation registered under the scheme. Enrollment continues to grow. Policymakers intend to enroll 750,000 installations in the scheme by 2020 (DECC 2010). Still, with 20 million households in England and Wales PV has achieved nothing close to the penetration rates of mobile phones or refrigerators for example.

[2] Total plant generating capacity in the UK in 2012: 89,000 MW.

Figure 1: FiT registrations: weekly and cumulative



Note: spikes in the weekly rate of new FiT installation registrations in the left panel reflect installation owners rushing to register their installation with the scheme ahead of a scheduled reduction in the tariff rate (payable for at least 20 years). In the right panel: it is intended that cumulative installations will rise to 750,000 by 2020.

Abrupt changes to the tariff schedule caused the weekly registration rate to fluctuate dramatically during the first three years (see Figure 1). By the second quarter of 2011 policymakers had become aware that the rate of uptake was exceeding expectation. This was being driven by a faster than expected fall in the cost of an installation, particularly solar PV. Policymakers became concerned about oversubscription and moved to attenuate the rate of uptake by revising the tariff structure downward (Ofgem 2011; Ofgem, 2012).

The announcement that tariffs would be reduced caused installation owners and installer companies to rush to register their installations before the reduction date. This rush-to-register behavior destabilized the FiT scheme at several points during 2011 and 2012. Policymakers had to exercise 'fast track' authority to bring the scheme under control. Tariff reduction announcements eroded confidence in the policy framework, which stoked rush-to-register behavior that made the oversubscription problem worse, provoking more tariff reduction announcements in a damaging negative feedback loop. By 2012 a more predictable reduction schedule had been implemented and the uptake rate had stabilized.

How good an investment is a household PV installation under the FiT scheme? Better in April 2010 than in March 2013 it would seem. Returns are driven by two main factors: the per kWh generation tariff and the installed cost of capital. The generation tariff is easily observable across the two time periods. The change in the installed cost of capital is not. In a review of the FiT scheme in autumn 2011 the government estimated that the installed cost of a typical 2.6 kW domestic installation had fallen by at least 30 percent in real terms since February 2010 (DECC 2011: 16). Others estimate that global solar PV prices declined by 16 percent per year in 2010 and

2011 due to the entrance of Chinese manufacturers and industry overcapacity (Aensen et al 2012). In the long view, the price of a watt of solar PV capacity has fallen by 4 percent per year on average since 1975. The table below shows that PV installation returns tended to be better in April 2010 than in March 2013 under any of these assumptions about the declining cost of capital.

Table 1: Estimated return on a domestic PV installation, April 2010 and March 2013

	April 2010	**March 2013 (-12% cost decline)**	**March 2013 (-30% cost decline)**	**March 2013 (-40% cost decline)**
Expenditure				
PV installation (£)	£12,500	£10,230	£8,138	£4,541
Annual operating cost (£)	£70	£65	£65	£65
Installation				
Capacity (kW)	2.6	2.6	2.6	2.6
Estimated annual output per kW (kWh)	850	850	850	850
Estimated annual output (kWh)	2,210	2,210	2,210	2,210
Tariffs				
Generation tariff (£/kWh)	£0.41	£0.11	£0.11	£0.11
Export tariff (£/kWh)	£0.03	£0.03	£0.03	£0.03
Bill savings (£/kWh)	£0.12	£0.13	£0.13	£0.13
Income				
Average net annual income (£)	£1,002	£352	£352	£352
Annual return on capital (%)	7.91%	3.30%	4.15%	7.44%

Note: 2010 prices. Assumes electricity consumption by a typical household of 4,500 kWh per year for an annual bill of £585. Annual operating cost, output and bill savings figures come from Ares et al 2012. PV cost decline refers to the estimated decline in the capital cost of a PV installation.

4. Distribution of policy costs

Total FiT payments made by all electricity suppliers together increased from £10.5 million in the first year of the scheme to £497.2 million in the third. Looking forward and assuming no major policy changes, a payment level of at least £500 million will remain in place until 2033. The regulatory impact assessment estimated that the FiT scheme will cost £8.6 billion overall by 2030 (DECC 2010).

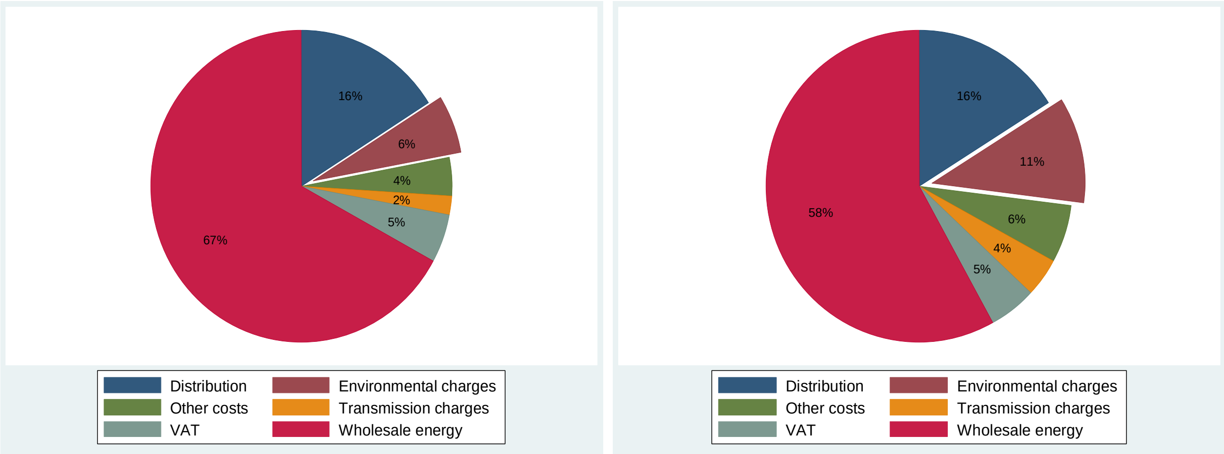
We examined the legal framework governing the policy to understand how these costs are being distributed. The distribution of the cost of the scheme needs to be understood alongside the distribution of the benefits to evaluate the full distributional incidence. Electricity suppliers pass on the cost of making FiT payments to their customers. FiT payments are paid for by electricity customers and not by tax payers. This is important because if the scheme was being paid for out of income tax revenue then there would be some assurance that better-off households were contributing more to the policy than worse-off households since income tax is raised in a generally progressive way.

Under the FiT scheme however electricity suppliers are authorised to spread the cost of FiT payments across their electricity customers according to a cost-spreading formula that they themselves decide. The policy is paid for by electricity customers through their electricity bills and not by the British government out of tax revenues. An attractive feature of this funding method from the point of view of the government is that the scheme is effectively 'off book'. This funding method also means that the electricity suppliers and not the government decide how the cost of the scheme is distributed.[3]

We discussed with several civil servants who designed and administered the policy whether the government had or has in place any guidance to the electricity suppliers on how the cost of the scheme should be distributed. The individuals we spoke with were not aware of any. We contacted the finance departments of three electricity suppliers and unsurprisingly none was willing to discuss its cost spreading formula. We are substantially concerned by this aspect of the policy. We are concerned that by passing responsibility to the electricity suppliers to determine how the cost of the policy is spread, the policy relinquishes government of the authority to ensure cost distribution is equitable.

[3] It seems that the Government did not deliberately relinquish authority for the cost distribution by setting out in legislation that this would be the remit of the electricity suppliers. Rather, it seems that by not dealing with the question of who would be responsible for the cost distribution question, responsibility has fallen to the electricity suppliers by default.

Figure 2: Environmental charges in a typical UK gas and electricity bill



Note: the cost of the FiT scheme is born not by central government but by electricity bill payers. According to Ofgem environmental programs like the FiT scheme accounted for approximately 11 percent of the average UK electricity bill in 2013 (2013b).

We compared the cost distribution arrangements under the British FiT scheme to that under similar FiT policies in Australia and California: the Australian Solar Homes and Communities Program (the Australian program) which ran from 2000 to 2009, and the California Solar Initiative (the California program) which runs from 2007 to 2016. We find that the British FiT is the only policy that does not take steps to guard against a negative distributional incidence.

4.1. Cost distribution in Australia

The Australian program had similar objectives to the British FiT: to promote the uptake of renewable energy, to reduce greenhouse gas emissions, to help the development of the Australian solar PV industry, and to increase public awareness and acceptance of renewable energy (Australian Government, 2006; Australian National Audit Office, 2010). The Austrlian program offered an upfront rebate to registered installation owners of between AUD 4 and AUD 8 per watt up to a maximum of AUD 8,000. The full rebate was paid directly to the installation owner within six weeks of registration. 109,000 installations were registered over 10 years (128 MW) with the vast majority at domestic premises. The Australian National Audit Office estimates the total lifetime cost of the program at AUD 1.1 billion (Australian National Audit Office, 2010).

The Australian program was paid for out of the national environmental expenditure budget under an agreement reached in 1999 called ‘Measures for a Better Environment’ (Hill, 2000; Macintosh and Wilkinson, 2010). The cost was born by tax payers and not by electricity bill payers. While there is evidence that better-off households participated more in the program than worse-off households [4], they also paid more into the general fund pot to support it. Towards the end of the program the Australian government also introduced a means test in the rebate application process, partly to deal with oversubscription issues and partly to answer criticism about disproportionate participation by better-off households. The means test limited eligibility under the program to households with a combined annual taxable income of less than AUD$100,000 (Australian Government, 2008).

4.2. Cost distribution in California

The aims of the California Solar Energy Initiative are to deploy solar PV and solar thermal capacity, promote research and development in solar technologies, and promote uptake among households living in affordable housing units. By the end of Q1 2013, 156,704 installations had been registered (1,621 MW), mostly at domestic premises (California Solar Statistics, 2013). Two types of incentive are offered: one which rewards the output of PV electricity, the other which rewards the installation of PV equipment. The total program budget was set at USD 2.167 billion and authorized by the California legislature (CPUC, 2013).

Similar to the British FiT, the CSI is paid for through customer electricity bills. However ten per cent of the budget (USD 216 million) is set aside to promote uptake by low-income households with the aim to install 190 MW of capacity among this demographic by 2016. The low-income provision was set out in the legislation that enabled the program. Incentives are more generous under the low-income provision and they do not decrease over time as the general incentive does. Households whose income is less than 50 per cent of the area mean can qualify for a highly subsidized installation and households whose income is less than 80 percent can qualify for a fully-subsidized installation.

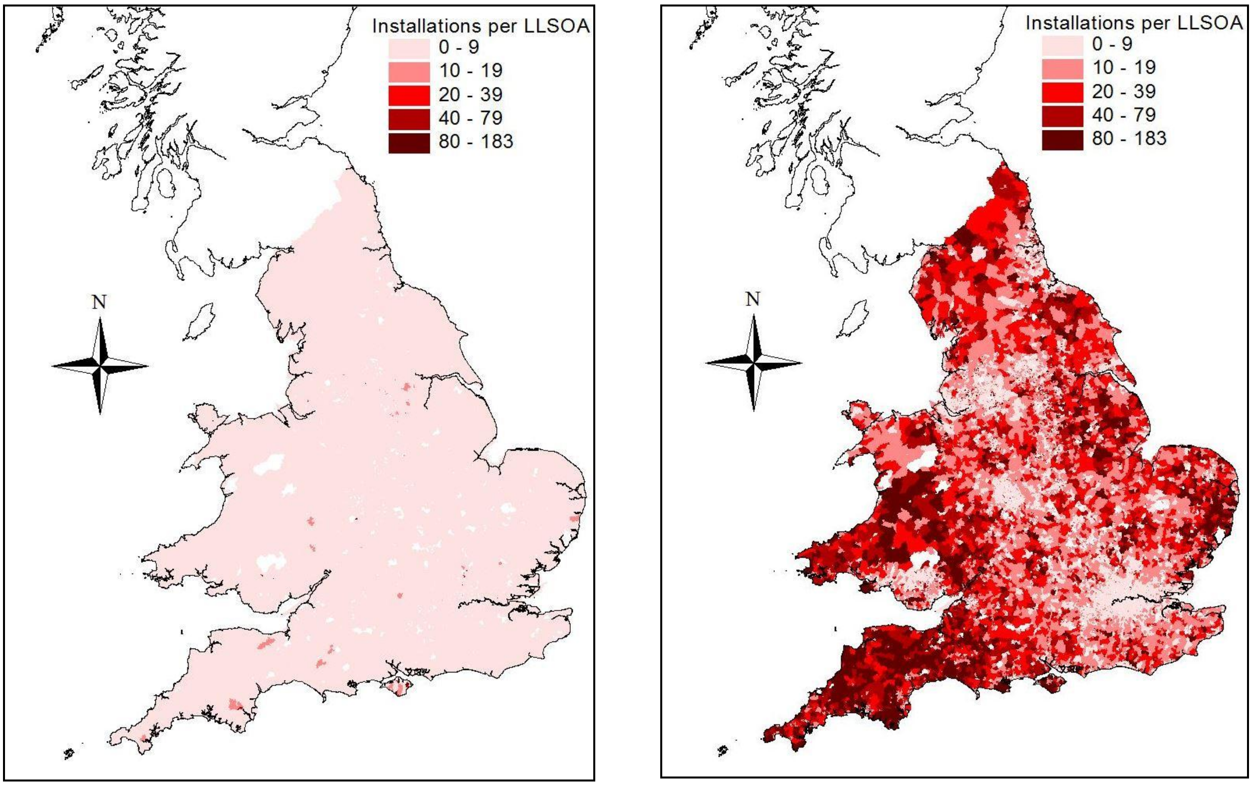
5. Distribution of policy benefits

To understand which types of households are benefitting from the British FiT we matched the data on all registered domestic PV installations located in England and Wales to 2011 census

[4] One study found that 66 per cent of all successful applicants under the Australian program resided in postcodes rated as medium-high or high (better-off) by the Australian Bureau of Statistics' Index of Relative Socio-economic Advantage and Disadvantage (Macintosh and Wilkinson 2010). Uptake seems to have been more equitable in the early years of the program. In the first two years, 25 per cent of successful applicants resided in postcodes that fell in the first quartile of the socioeconomic status distribution (best-off). By the last two years this number had fallen to 11 per cent, implying that less well-off households adopted later.

data, on the basis of lower layer statistical output areas (LSOAs) – small statistical geographies.[5] This allows us to observe the socioeconomic characteristics of all households in aggregate in the neighborhoods where installations are located.

Figure 3: Domestic PV installations, April 2010 and March 2013



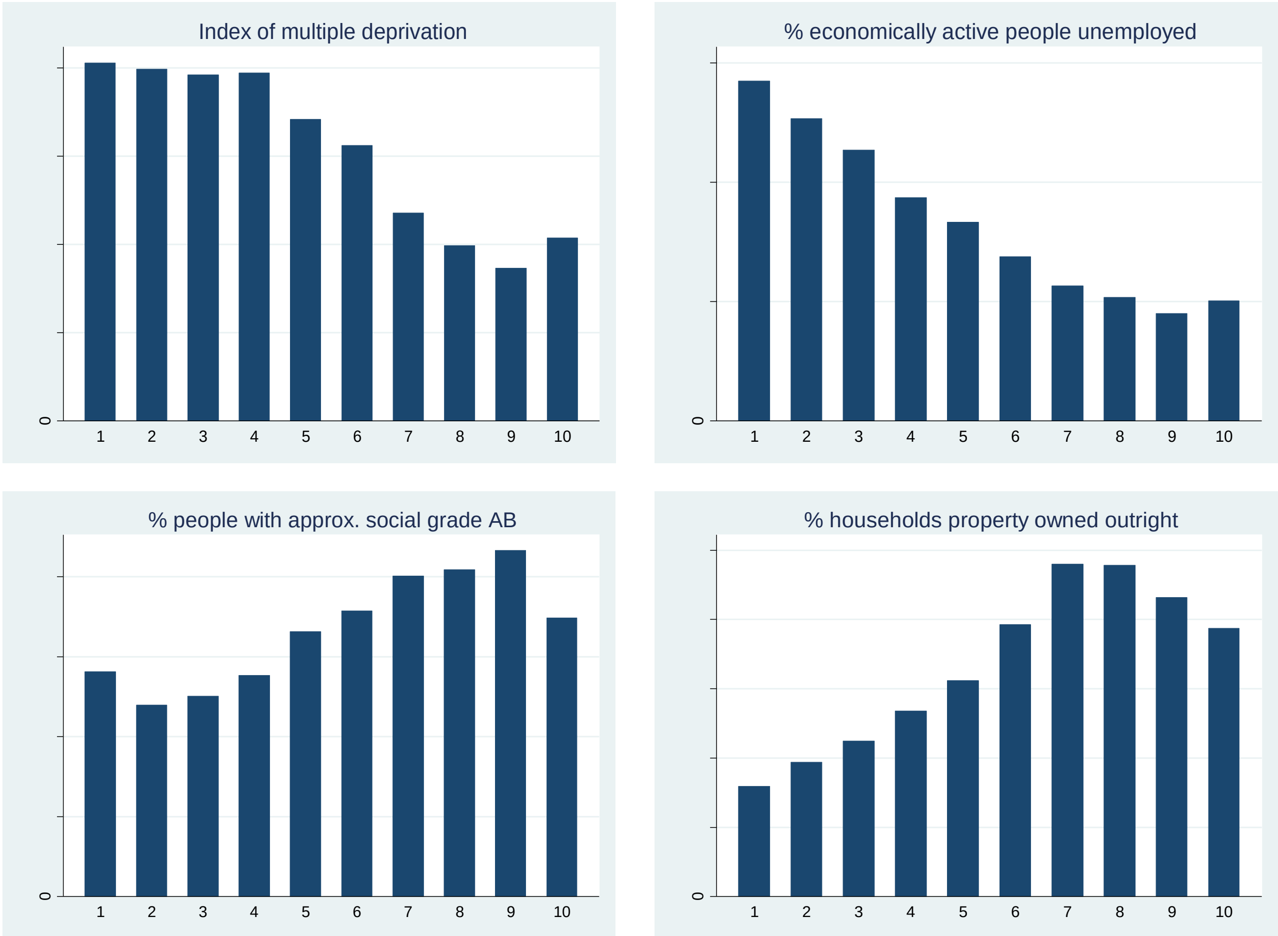
Note: the distribution of FiT-registered PV installations across the 34,090 LSOAs in England and Wales (installations smaller than 50 kW only). Installations concentrate in relatively southern regions where solar radiation gain is greater and the return on investment in a PV system is higher. They also concentrate in peripheral areas where population density is lower.

In the first three years a relatively small number of PV installations located in urban areas such as greater London and a relatively high number have located in rural, peripheral, and southern areas. Greater annual solar radiation gain at southern latitudes improves the return on a PV investment. More installations in southern regions draws attention to the pre-existing distributional tension in the UK between the relatively prosperous southern regions with their service-based economies and the less prosperous northern regions that are feeling the effects of deindustrialization more acutely (Martin 1988, Massey 1996).

[5] Installations in Scotland were excluded from the match for census data compatibility reasons. In 2011 the average population of an LSOA in England and Wales was 1,614 and the mean number of households 672. There are 34,090 LSOAs in England and Wales.

Installations have tended to locate in more prosperous areas. The top two panels below show more installations in the lower LSOA deciles for indicators of the absence of prosperity (index of multiple deprivation, perc. economically active people unemployed). In the bottom two panels there are fewer installations in the lower deciles for indicators of the presence of prosperity (perc. people social grade AB, perc. households owning property outright).

Figure 4: Installations counts for four prosperity indicators, by LSOA decile



Note: FiT-registered domestic PV installations for four prosperity indicators, by decile. In the top left panel, about 20,000 more installations are located in low deprivation areas (1st decile) than in high deprivation areas (10th). Indicators of the *presence* of prosperity in the bottom two panels show the same pattern, in reverse.

We initially exploit just the spatial dimension in our data, to estimate the relationship between installation uptake and the socioeconomic characteristics of households across LSOAs. We construct a simple empirical model to examine the relationship between the economic prosperity variables and the number of installations having located in each area. The dependent variable in these estimations is the number of PV installations smaller than 50 KW, a count. We chose a count measure over a KW-installed measure because counts correspond better to the decision-making unit of interest, which we take to be the individual household. The unit of analysis across all variables is the LSOA, the statistical geography described above. The table below gives descriptive statistics for the dependent variable and all continuous independent variables included in the model.

Table 2: Descriptive statistics

	N	mean	p50	min	max	sd
Installations per HH	34,378	14.24	8.56	0.00	284.64	17.54
Installed kW per HH	34,378	45.67	26.09	0.00	881.18	56.62
Income per HH, annual	34,378	15.34	8.45	0.00	267.19	19.44
Income per HH, lifetime	34,378	380.50	208.04	0.00	6,679.71	483.94
Residents per hectare	34,378	41.15	33.23	0.03	684.70	41.09
Perc. HHs where everyone speaks English	34,378	91.25	96.44	14.50	100.00	12.08
Installer companies in MSOA	34,378	0.46	0.00	0.00	7.00	0.80
Perc. HHs owning property w/ mortgage	34,378	33.21	33.76	0.76	78.48	10.59
Perc. people unemployed	34,378	4.40	3.70	0.24	20.46	2.43
Perc. HHs no central heating	34,378	2.60	2.08	0.00	34.11	2.09
Perc. people social group AB	34,378	22.67	20.38	1.23	73.95	12.94
Perc. people highest education level	34,378	26.67	24.87	3.30	82.15	12.39

Density controls for a factors that would discourage the uptake of PV installations, as through there being a limited amount of surface area to capture solar radiation in areas where people per hectare is high. The percent of households owning their home outright controls for households that would have passed the first stage of the theoretical household PV adoption process discussed above. The index of multiple deprivation, per cent unemployment, and per cent of people in social group AB are the test variables of interest but, since they are likely to be collinear, we include them separately as individual test of the broader hypothesis about installation uptake across socioeconomic strata. Installer companies per MSOA controls for the amount of information exposure through marketing ‘push’ different households may have been exposed to. This variable is measured as the number of registered PV installer companies that were located in the Middle Layer Super Output Area (MSOA) that contains the LSOA. An MSOA is the next largest statistical geography after the LSOA.[6]

[6] There are 7,201 MSOAs in England and Wales. An MSOA contains around five time as many households as an LSOA.

Cross sectional variation in return on capital comes from quantity of capital invested in over all households in each LSOA, the tariff level which is linked to the size and type of installation, and the either 20 or 25 year policy contract according to whether capital investment occurred before or after XXXX. There is also time variation, in the tariff level within installation types as the tariffs changed (degressed) over time.

If the data supports the hypothesis that early adopters had greater net gains, and that early adopters tended to be richer overall, then the month dummy coefficients should be bigger in early months and smaller in later months. A further approach is to interact social class with month dummies or with a time trend or with a variable capturing time-to-adoption for all installations within an LSOA. Early month dummies should shift the slope with social class upward, increasing the return to capital. The expectation is that the impact of social class on annual income depends on timing. That is, the way social class confers advantage is through timing – not just earliness but through calibration to market conditions, e.g. the confluence of PV capital cost, tariff policy, durability and certainty of the contract under the contract with government under policy regime, etc.

For the dependent variable, income per household within each LSOA is calculated in three steps starting with income at the level of the installation. This is essentially the expected return on investment to a PV capital investment over the full 25 year life of the investment:

$$V(i) = \omega(i)(t) - [\eta(i) * \lambda(j) * \pi] * \psi(i)$$

Where *V(i)* is the expected net return to installation (*i*) over the total investment lifetime, ω is the capital cost of installation (*i*) at time (*t*), η is the size of installation (*i*) measured in kW of generation capacity, λ is annual solar radiation gain in LSOA (*j*), π is the contract period under the policy that defines the investment lifetime (25 years for installations registered up to March 31, 2012 and 20 years thereafter), ψ is the tariff rate paid to installation (*i*) for each kWh of electricity generated, the value being fixed for the total investment lifetime. Expected net return to each installation is summed for all installations in each LSOA (*j*) giving total expected net return to all the households in each LSOA:

$$V(j) = \sum_{(i)} V(i)$$

Finally, net return to all installations in each LSOA is normalized by the number of households to calculate net return per household in each LSOA, the level at which we are able to observe socio-economic characteristics:

$$R(j) = \frac{V(j)}{H(j)}$$

The general form of dependent variable R(*j*) can be expressed in terms of net return per household per LSOA, net annual return per household per LSOA, installations per household per LLSOA, and installed capacity per household per LSOA.

We include local authority dummies to control for location-specific factors. The local authority is the lowest level of government in Britain and there are 347 in England and Wales. Location-specific factors that could influence PV uptake are numerous. The restrictiveness of local planning laws could determine how easily a household receives planning permission for an installation (where permission is necessary). Differences in annual solar radiation gain across southern and northern regions change the attractiveness of a PV investment. Electricity prices may vary across electricity supplier companies' service territories. It is generally less expensive to integrate a PV installation to a property that is being built anew than to install it on an existing property. More installations may be being installed in areas where the housing stock is rapidly expanding or rapidly being replaced (Scarpa and Willis 2010). Local authority fixed effects mean that we are testing for a relationship between PV installations and economic prosperity within local authorities.

We fit these data to the following reduced form empirical model, where *I* denotes net income to all households in each LSOA and subscript *i* denotes the area (LSOA).

$$I_i = \alpha_i + \boldsymbol{\beta}' P_i + \boldsymbol{\zeta}' C_i + \varepsilon_i$$

Further, α is the intercept, P is a vector of test variables denoting the economic prosperity level of the area (the variables of interest), C is a vector of control variables (density, homeownership, installer companies, and the 348 local authority dummies), and ε is an i.i.d. error term. The coefficients $\boldsymbol{\beta}'$ on the test variables are of main interest in the estimations. Specification (1) of table 6 regresses the count of PV installations on density, homeownership, and installer companies with the local authority fixed effects initially excluded. All of control variables take the expected signs. Specifications (2) – (4) include the local authority fixed effects as well as the three test variables in turn: percent of people in social group AB, the index of multiple deprivation, and percent of people unemployed. The evidence in this first set of regression supports the idea that worse off areas associate with fewer PV installations, all else equal.

Table 3: Regression estimates

	(1) Installations per HH	(2) Installed kW per HH	(3) Income per HH (annual)	(4) Income per HH (lifetime)
Residents per hectare	-0.088**	-0.339**	-0.116**	-2.880**
	(0.023)	(0.098)	(0.034)	(0.837)
Perc. HHs where everyone speaks English	0.076*	0.040	0.010	0.243
	(0.034)	(0.104)	(0.037)	(0.909)
# installer companies in MSOA	0.543**	2.648***	0.951***	23.736***
	(0.155)	(0.591)	(0.199)	(4.922)
Perc. HHs owning property w/ mortgage	-0.049	-0.198	-0.087	-2.199*
	(0.040)	(0.120)	(0.042)	(1.043)
Perc. people unemployed	-0.743***	-3.741***	-1.447***	-36.077***
	(0.185)	(0.455)	(0.163)	(4.083)
Constant	11.973*	62.304***	23.548***	589.117***
	(4.316)	(15.375)	(5.542)	(138.286)
Local authority dummies	Yes	Yes	Yes	Yes
Obs	34090	34090	34090	34090
R-square	0.350	0.391	0.403	0.402
Adj. R-square	0.343	0.385	0.397	0.396
Df	18	17	17	17

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Errors clustered on electricity supplier territories.

In the second set of regressions we begin to investigate the time dimension of the uptake process by estimating the number of PV installations that located in each area during three different periods. Recall Figure 1 above showing how the number of PV installations registered under the scheme changed by week. Recall the registration spikes that were caused by, and which themselves caused, instability in the FiT program as installation owners rushed to register their installations ahead of downward revisions to the tariff schedule. In the table below we estimate the relationship between an index of multiple deprivation and all PV installations registered under the program for each of the first three years. Specification (1) is the baseline and the same as specification (3) in table 6 above. Specification (2) restricts the dependent variable to include only those installations that registered under the program until the beginning of the period of instability, so April 2010 to October 2011. We also modify the installer companies control variable to reflect only the installer companies that existed in the MSOA in the first period. Specification (3) restricts the dependent variable to only those installations that registered between November 2011 and April 2012, the rush-to-register period. Specification (4) restricts the dependent variable to the installations that registered between May 2012 and March 2013.

Table 4: Regression estimate by period

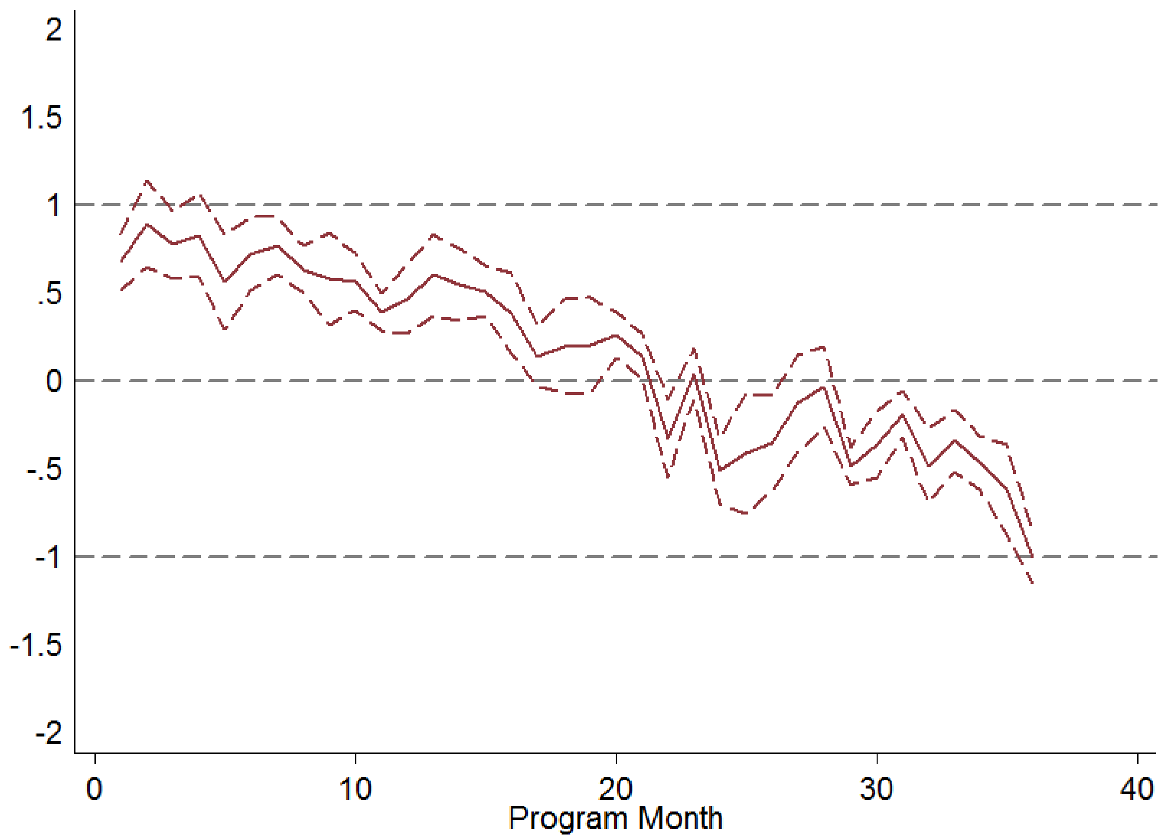
	(1) Combined	(2) Early period	(3) Mid period	(4) Late period
Density (people/hectare)	-0.0123***	-0.0147***	-0.0134***	-0.0114***
	(0.000203)	(0.000285)	(0.000306)	(0.000254)
Perc. households owned outright	-0.0792	-0.781***	-0.665***	0.856***
	(0.0689)	(0.0880)	(0.0988)	(0.0824)
Index of multiple deprivation	-0.00860***	-0.0255***	-0.0124***	0.00184***
	(0.000523)	(0.000708)	(0.000770)	(0.000628)
Installer companies in MSOA	0.0899***			
	(0.0153)			
Installer companies in early period (cumulative)		0.224***		
		(0.0642)		
Installer companies in mid period (cumulative)			0.140***	
			(0.0238)	
Installer companies in late period (cumulative)				0.0337*
				(0.0188)
Constant	2.690***	2.323***	1.655***	1.127***
	(0.129)	(0.160)	(0.184)	(0.158)
Observations	32,201	32,201	32,201	32,201
Local authority dummies	Yes	Yes	Yes	Yes

Dependent variable is (1) all PV installations that registered from April 2010 to March 2013; (2) installations registered from April 2010 to October 2011 (early period), (3) installations registered from November 2011 to April 2012 (mid period), (4) installations registered from May 2012 to March 2013 (late period). Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The index of multiple deprivation continues to take the expected negative sign across all four specifications: areas with higher levels of deprivation are registering fewer PV installations. Comparing the magnitude of the coefficient on that variable in specification (3) to the magnitude of the coefficient in the other specifications, shows that the effect of the index of multiple deprivation was actually weaker during the rush-to-register (mid) period of the FiT program. Deprivation deterred PV installations strongly in the early period, and moderately in the late period, but relatively weakly in the middle period. One possible reason for this, which we are exploring now, is that installer companies marketed PV installations more strongly during the rush-to-register period since they were some of the main beneficiaries of the high tariff rates. While households may have selectively chosen to adopt in the early period, the installer companies may have sought out households more or less indiscriminately during the rush-to-register period, including some worse-off households that might not otherwise have participated.

Although our results are still preliminary, we also tried estimating the relationship between PV installations and the index of multiple deprivation for each of the 36 months we observe uptake under the program. This makes it possible to see how the coefficient on the index of multiple deprivation changes over time. Figure 4 plots these coefficients.

Figure 5: Index of multiple deprivation coefficient by program month



Note: coefficient on index of multiple deprivation estimated and plotted for each of 36 months (cross sections) of the installations / census dataset.

Uptake of the FiT scheme has so far been skewed away from areas in England and Wales where households are relatively poor. This is not the same thing as saying that FiT installation owners tend to be better off, or that rich households are more likely to benefit from FiT payments than poor households, or that rich households are benefitting from a disproportionate share of total FiT payments. However, this analysis points strongly toward these conclusions.

6. Findings and conclusions

The available evidence implies that uptake of the FiT scheme during its first three years has been significantly skewed away from poor households and that poor households are receiving a significantly smaller proportion of total FiT payments than they would if uptake across income groups were uniform. This is not because the FiT scheme itself is skewing uptake but because poor households are less able to participate in the scheme for reasons related to dwelling type, technology type, spatial location, and capital access. The lack of transparency on the cost distribution side of the scheme is concerning.

We estimate based on conservative assumptions[7] that the less prosperous half of British households receives between £14.2 and £26.6 million less per year in FiT payments than they would if uptake were perfectly distributed across income groups. By this calculation the more prosperous half of households is benefitting disproportionately by the same amount. Over 20 years of FiT payments this would amount to between £284 million and £532 million.

While our results in this draft working paper are very preliminary we believe they may shed more light on the relationship between new technology, the increasing pace of technological change, and social inequality.

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[7] For any indicator in Figure 3 calculate the mean number of installations per decile. Subtract this from the number of actual installations in each decile giving the difference between perfectly equitable uptake across income groups and the status quo. Taking the sum of differences for income groups below the median gives the estimated 'installation deficit' relative to the mean. The average FiT payment per year per installation is assumed to be £500. On the cost side the assumption that the electricity suppliers spread the cost of the scheme perfectly across bill payers according to their ability to pay. Calculations available from the author.

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