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Friends with benefits: How income and peer diffusion combine to create an inequality "trap" in the uptake of low-carbon technologies

Fraser Stewart

University of Strathclyde, McCance Building, Richmond Street, Glasgow, G1 1XQ, Scotland, United Kingdom

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ABSTRACT

What drives inequalities in the uptake of low-carbon energy technologies? Research has shown that people on higher incomes are significantly more likely to access and benefit from policies designed to boost uptake of clean energy technologies than those with lower incomes, revealing a pervasive inequality issue. Yet little is known about how these inequalities evolve or interact with factors beyond income alone, understanding of which is crucial to designing policies which do not simply replicate or exacerbate existing inequalities going forward. This paper thus advances the novel "feed-in-tariff trap" theory, which posits that, rather than income alone, peer diffusion and socioeconomic factors compound to widen inequalities in the uptake of low-carbon technologies over time. Using a combination of mixed effects and piecewise structural equation modelling, this theory is tested on the adoption of 21,206 household-level wind and solar PV installations across 6976 micro-level data-zones in Scotland between 2009 and 2020 under the UK government feed-in-tariff. It finds crucially that: (1) household solar PV and wind are adopted consistently in higher-income areas, (2) peer diffusion is strongest in higher income areas with high early adoption rates, and (3) socioeconomic conditions are extremely temporally stubborn. Combined, this trifecta creates an inequality "trap", locking the benefits of low-carbon technology subsidies into the same higher income areas and widening the gap in uptake between more affluent and deprived communities as a result. Recommendations are given on how best to address this, with implications for anyone concerned with a "just" transition going forward.

1. Introduction

With the "just transition" to net zero now front-and-centre of national and international energy ambitions, understanding who gets to access and reap the benefits of clean energy policies across societies is crucial to ensuring that this transition is both fair and equitable (Colli, 2020; European Commission, 2020; Heffron and McCauley, 2018; Jenkins et al., 2018; McCauley et al., 2019a). Low-carbon technology incentive schemes, such as feed-in-tariffs, have been especially effective in encouraging citizens to reduce the carbon footprint in their homes through installing small-scale, clean energy generation technologies like household solar PV and wind turbines (Castaneda et al., 2020; Cherrington et al., 2013). Feed-in-tariffs incentivise the uptake of these technologies by effectively paying people for the clean electricity that they generate, which in turn can provide substantive social and economic benefits for participants (Balta-Ozkan et al., 2015; Curtin et al., 2018; Grover and Daniels, 2017; Hitaj and Löschel, 2019; Winter and Schlesewsky, 2019). Beyond mitigating CO_2 emissions, research suggests that feed-in-tariffs can provide people with additional income, reduce energy bills and help to alleviate fuel poverty, with related second-order benefits for health, social capital and wellbeing (Berka et al., 2020; Kosugi et al., 2019; Kucher et al., 2020; Richler, 2017; van der Waal, 2020).

For these benefits, however, accessing policies like the feed-in-tariff (or any similar grant, subsidy or loan scheme designed to promote the uptake of clean energy technologies among citizens) can be expensive in time, knowledge and money (Balta-Ozkan et al., 2015; Coffman et al., 2016; Fikru, 2020; Lukanov and Krieger, 2019; Sunter et al., 2019). Making use of such policies generally requires people to own their homes, while most still also incur an upfront time and financial cost (Rai et al., 2016; Richler, 2017; Sommerfeld et al., 2017). As such, higher income groups are distinctly better placed to access and benefit from such initiatives than those living on lower incomes or experiencing poverty and deprivation, creating a persistent and pervasive issue of inequality and energy justice (Lacey-Barnacle, 2020; McCauley et al., 2019b; Sovacool et al., 2019). Research has confirmed that this inequality exists in a number of places, with lower-income groups and communities found to be less likely to access and benefit from domestic

E-mail address: fraser.jf.stewart@strath.ac.uk.

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energy initiatives in the US, Australia, Italy, Tokyo, Switzerland, Sweden, the UK and others (Coffman et al., 2016; Fikru, 2020; Kucher et al., 2020; Kwan, 2012; Li and Yi, 2014; Lukanov and Krieger, 2019; Sommerfeld et al., 2017; Sunter et al., 2019; Wolske, 2020). This inequality poses a fundamental problem for governments concerned with ensuring a just transition: because technologies supported by grants and subsidies can have substantive social and economic benefits for users, the concentration of those benefits within mid- and high-income groups risks repeating and further exacerbating existing socioeconomic inequalities.

Understanding how these inequalities emerge and evolve is thus essential to ensure that opt-in grant and subsidy schemes designed to promote the uptake of new, low-carbon technologies do not simply become mechanism of replicating or exacerbating existing injustices. In addition to cost, however, informational barriers also exist around accessing grant and subsidy schemes, such as knowing about the policy in the first place, how to initiate action, where to find up-front finance if required, technical capacity and knowledge of the installation process, along with who to approach as trusted installers and intermediaries to conduct the work. One way in which these informational barriers can be overcome is through peer diffusion. Previous empirical research has found consistently that areas with already-high rates of uptake are more likely to see new capacity added than places where uptake has not previously occurred, through the influence of early adopting peers and neighbours who can help to inform others about relevant bureaucratic processes, connect them with experienced actors, convey the benefits and reduce informational uncertainties (Bach et al., 2020; Bollinger et al., 2012; Busic-Sontic and Fuerst, 2018; Carattini et al., 2018; Korcaj et al., 2015; Rai et al., 2016; Richter, 2014; Snape, 2016; Thormeyer et al., 2020).

While typically held apart in empirical work, however, it follows that peer diffusion can contribute to widening socioeconomic inequalities, since higher incomes within a group or area increases the likelihood of uptake in the first instance, *which in turn creates scope for peer diffusion to take place*. Combined with socioeconomic circumstances being persistent over time, these factors create an environment whereby early inequalities in grant, loan or subsidy access can be locked in, leaving social and economic benefits of these policies concentrated strongly within already higher-income groups at the perpetual exclusion of those on lower incomes (who arguably also stand to benefit the most from payments or savings). Considering these factors together is essential to creating a more complete picture of the social and economic processes that cause inequalities to emerge and widen not just in feed-in-tariffs but in any opt-in, subsidy or decentralised innovation initiative, to ensure policymakers are equipped to create a fully "just" transition going forward.

To help understand this process, this paper thus advances a novel "feed-in-tariff trap" theory, which posits that socioeconomic factors and peer diffusion combine to effectively "trap" socioeconomic inequalities in low-carbon technology uptake over time. Using a combination of mixed effects and piecewise structural equation modelling, this theory is tested on 21,206 household-level solar PV and wind feed-in-tariff installations across 6976 data-zones in Scotland between 2009 and 2020. Analysis shows that (1) household solar PV and wind are adopted consistently in higher-income areas, (2) peer diffusion is strongest in higher income areas with high early adoption rates, and (3) socioeconomic conditions are extremely temporally stubborn. These findings lend considerable support to the feed-in-tariff trap theory, revealing that that financial and social factors which drive access inequalities are interlinked and temporally persistent, with stark implications for anyone concerned with ensuring that the design of policies geared towards net zero are fair and equitable in future.

This paper makes two significant contributions to the literature. First, it demonstrates that inequalities in feed-in-tariff access are not simply a static function of disparate economic or social mechanisms, but that these factors are both connected and stubborn. This is important: subsidized initiatives which rely on people accessing services themselves are vulnerable to this combination of deprivation and diffusion creating similar inequality traps, and so understanding this relationship can help to avoid such issues in future, particularly as efforts to encourage households to install heat pumps and energy efficiency measures are increased (UK Government, 2020a). Second, it introduces a novel piecewise structural equation approach, which can be a powerful tool for more robustly unpacking causal mechanisms and complex theories within the wider energy policy field (Lefcheck, 2016a). To the author's knowledge, piecewise structural equation modelling has not yet been applied within mainstream energy policy literature, and so this serves as an innovative and powerful contribution for promoting novel theory-testing approaches that are often found lacking in the discipline (Sovacool et al., 2020).

2. Theory

Both income and peer diffusion have been found to be separately important mechanisms in driving the adoption of household solar PV and wind technologies under the feed-in-tariff and similar policies. Income has been found to be an especially powerful determinant of household solar PV uptake in a number of locations. People with higher incomes and in higher-income areas have been found to be more likely to adopt household solar PV than lower income groups in the US, Australia, Italy, Tokyo, Switzerland, Sweden, the UK and others (Coffman et al., 2016; Fikru, 2020; Kucher et al., 2020; Kwan, 2012; Li and Yi, 2014; Lukanov and Krieger, 2019; Sommerfeld et al., 2017; Sunter et al., 2019; Wolske, 2020), revealing a fairly widespread and entrenched socioeconomic inequality. Beyond financial means alone (which are of course fundamental), this disparity is linked to a number of different mechanisms. Lower income groups are less likely to own their homes and often live in built-up urban areas, creating issues of capacity for installation both legally and physically, while people who live in poverty are typically more concerned with more immediate basic needs like affording food and housing, in addition to dealing with the psycho-social stresses that poverty itself can create (McDonald et al., 2020). Under these conditions then, and with the steep up-front costs of installing new energy systems, finding the time and resources to navigate administrative policy and installation processes can be a monumental challenge (Balta-Ozkan et al., 2015; Coffman et al., 2016; Fikru, 2020; Lukanov and Krieger, 2019; Sunter et al., 2019). Environmental justice research reveals that these inequities also have gendered, racial and health dimensions (Lukanov and Krieger, 2019).

Beyond these well-established socioeconomic inequalities, however, significant informational barriers also exist in accessing grant and subsidy initiatives: people interested in utilising any such policy require some degree of political efficacy to know how to initiate action, while knowing how to then navigate the installation process, which suppliers can be trusted, and who to contact regarding tariffs and payments can be unclear in the first instance (Rai et al., 2016). One way in which these informational barriers can be overcome is through peer diffusion (Alipour et al., 2020; Bach et al., 2020; Balta-Ozkan et al., 2015; Bollinger et al., 2012; Busic-Sontic and Fuerst, 2018; Carattini et al., 2018; Korcaj et al., 2015; Richter, 2014; Thormeyer et al., 2020). Peer diffusion refers to the diffusion of ideas, practices or behaviours through social interactions within shared networks and communities (Bollinger et al., 2012; Wolske et al., 2015). This may be between neighbours, within similar social groups and networks of both place and interest, or through digital communication (Kloppenburg and Boekelo, 2019). In terms of low-carbon technologies, people within similar communities or social networks are more likely to install a solar PV system, for instance, where neighbours, friends or other members of that network have already done the same (Bollinger et al., 2012; Noll et al., 2014; Rai et al., 2016; Richter, 2014; Rode and Weber, 2016), or where charities and organizations are present and working to actively raise awareness (Balta-Ozkan et al., 2021). Members of a network, neighbourhood or community who have their own systems can stimulate diffusion by reducing uncertainty associated with technical, bureaucratic and financial processes, helping others within the network to overcome informational barriers, while the visible presence of installations within an area can also help generate wider interest (Rai et al., 2016; Rode and Weber, 2016; Wolske et al., 2015).

Empirical quantitative research into the effects of peer diffusion thus finds that previously installed low-carbon technologies or access to policies promoting this within in an area is strongly linked to the likelihood of future installations within the same area (Bollinger et al., 2012; Richter, 2014). This has been found consistently at the neighbourhood, post-code and county levels across various contexts (Bach et al., 2020; Noll et al., 2014; Rai et al., 2016; Thormeyer et al., 2020). While limitations exist in explaining diffusion beyond defined spatial units (since social networks are rarely confined to single geographical areas), evidence suggests that peer diffusion within geographic units is strong and persistent (Carattini et al., 2018; Thormeyer et al., 2020).

2.1. The feed-in-tariff trap

For this individual importance, however, it makes sense for these two factors to be considered together, especially for grant and subsidy schemes such as the feed-in-tariff which rely on people opting-in and initiating action themselves. Since peer diffusion relies on there being people within a neighbourhood or community who have already accessed the feed-in-tariff, and since higher income groups are more likely to access the feed-in-tariff at higher rates overall, it stands to reason that peer diffusion could effectively lock in or even exacerbate socioeconomic inequalities in feed-in-tariff access over time. Thought about practically, higher incomes/lower levels of poverty and deprivation increase the likelihood to access the feed-in-tariff in the first place (Coffman et al., 2016; Fikru, 2020; Kucher et al., 2020; Kwan, 2012; Li and Yi, 2014; Lukanov and Krieger, 2019; Sommerfeld et al., 2017; Sunter et al., 2019; Wolske, 2020), which in turn helps to reduce informational barriers within communities and neighbourhoods; create a network of trusted installers and intermediaries; reduce technical and policy uncertainties and ultimately create the potential for peer diffusion to happen (Rai et al., 2016; Rode and Weber, 2016; Wolske et al., 2015).

Conversely, in areas of higher poverty and deprivation, the scope for adopting new technologies is restricted by issues of ownership, poverty stressors and priorities and financial capacity, which means that the scope for diffusion to take place in future is also limited as a result: those networks are not established, and so informational barriers remain. This creates a *double disadvantage* for groups and areas experiencing higher levels of poverty and deprivation, in that two avenues for potential uptake are subsequently restricted. It thus follows that areas with lower levels of deprivation are more likely to access the feed-in-tariff *and in turn reduce informational barriers within these areas,* compared to areas with higher levels of deprivation, low levels of adoption and subsequently limited scope for diffusion.

Rather than the independent effects of these mechanisms, then, the intrinsic link between the two creates an environment wherein inequalities can be accelerated. The “feed-in-tariff trap” theory presented here thus aims to unpack this relationship (although the feed-in-tariff is the example used here, this can apply in principle to any grant, loan, or subsidy scheme designed to encourage uptake of low-carbon measures at the household-level). In essence, it posits that income and poverty levels predominantly determine the likelihood of adoption within a given locality, which in turn allows for peer diffusion to take place. If inequalities emerge among early adopters, then these inequalities can be compounded by peer diffusion. Combined with the temporally enduring nature of socioeconomic conditions (i.e. high-income areas tend to remain high-income areas while low-income areas tend to remain low-income over time), these effects create an inequality “trap”, whereby more affluent groups benefit from both socioeconomic capacity *and* the subsequent peer diffusion effects, while deprived groups are limited on both fronts, leading to extremely stubborn inequalities in feed-in-tariff access over time. Fig. 1 visualises this model more clearly.

In this figure, the horizontal arrows represent the link between each factor and the same factor at the previous time point (*KW* represents installed household energy capacity under the feed-in-tariff within a given area). The diagonal line represents the link between income and installed capacity. Across all time periods, lower income/higher levels of poverty and deprivation are associated with lower likelihood of household-level energy being installed under the feed-in-tariff. Previous levels of installed capacity then affect the likelihood of adding capacity in future through peer effects such as learning and word-of-mouth from neighbours, social networks and community members. Socioeconomic conditions as represented here by income is then linked to socioeconomic conditions within an area at *t-1*, *t-2* and so on. This final link is critical: the trap theory does not simply suggest that poverty or income and peer diffusion are both important determinants of feed-in-tariff access at any time point, but that socioeconomic conditions are also extremely stubborn over time. Because of this stubbornness, these inequalities in access to the feed-in-tariff can deepen and grow.

These relationships are finally hypothesized as:

H1. Higher-income areas are likely to have higher levels of domestic feed-in-tariff access than more deprived, lower-income areas.

H2. Areas where installed domestic feed-in-tariff capacity already exists are more likely to see new feed-in-tariff installations than areas with no prior installations.

H3. Previous income levels strongly predict future income levels.

3. Model

3.1. Piecewise SEM

To test the feed-in-tariff trap theory, piecewise structural equation modelling (SEM) was selected as a method with unique capacity for unpacking its component parts. Structural equation modelling is a form of path analysis that resolves complex multivariate relationships between variables (Lefcheck, 2016a). In terms of theory-testing, SEM is a powerful tool for understanding relationships beyond regression analysis alone (Bollen and Pearl, 2013; Shipley, 2016). This is because variables in SEM can take the form of both predictors and responses: SEM lends itself especially well to testing cyclical, bidirectional, cascading or mediating effects with multiple output variables, where traditional models tend towards more straightforward, independent linear analysis (Grace, 2008). In the case of the feed-in-tariff trap, relationships are expected between the same variables across several timepoints as both predictor and response, meaning that linear regression may run into issues of collinearity. SEM is thus preferred over a series of basic multiple regressions (although these are also tested for robustness across a number of different multi-level specifications, with results included in the Appendix).

Also known as confirmatory path analysis as initially proposed by Shipley (2009), Piecewise SEM is a particularly effective and computationally efficient version of SEM where latent variables are not incorporated (Lefcheck, 2016b; Shipley, 2016; Stenegren et al., 2017), as is the case here, and with in-built ability to deal with hierarchical and multi-level models. The root of piecewise SEM is a set of linear equations representing the individual paths between observed variables within the theoretical model, that are then pieced together and assessed for model fit within a single causal framework (rather than simply running a series of independent or multiple linear regressions on various different dependent variables). In this case, the theoretical model is captured in the paths outlined in the hypothesized “feed-in-tariff trap” from Fig. 1. The equations representing the paths between these models is given in section 4.4.

Within that causal framework, piecewise SEM goodness-of-fit

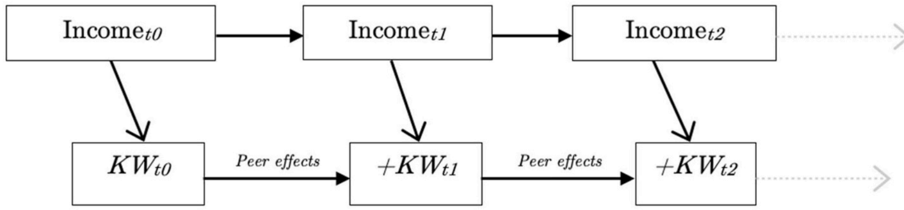

Fig. 1. The feed-in-tariff trap.

procedures consider the entire model together, rather than solely the statistical significance of single variables, meaning that the full theoretical model is tested for significance, rather than individual variables in isolation. That is, piecewise SEM goodness-of-fit measures test for significance in all possible directional relationships and pathways between all variables within a model, identifying spurious or "over-saturated" models using d-separation tests, and so models need to be carefully specified from robust and considered theory-building processes in advance (Zur et al., 2018). All specified response variables within the model are given coefficients and R^2 figures to assess significance of and variance explained by the specified relationships. Analysis was conducted using the piecewiseSEM package in R (Lefcheck, 2019).

4. Data

With government bodies such as the Just Transition Commission dedicated to ensuring an equitable path to net zero (Scottish Government, 2019), Scotland is a useful case in which to examine these inequalities. Through the Community and Renewable Energy Scheme (CARES), the Scottish Government have made a concerted effort to promote the growth of local, community and small-scale energy systems under the feed-in-tariff. The rapid growth in wider local energy systems from 204 MW at the start of the decade to over 750 MW installed capacity today is the result of ambitious targets (1 GW installed capacity by 2020, 2 GW by 2030) which were extended after the initial target of 500 MW installed capacity by 2020 was surpassed 5 years early (Energy Saving Trust, 2015). For this impressive feat, however, analysis conducted in 2013 suggested that income inequalities in access to local- and household-level energy were already emerging (Haggett et al., 2013). Given the rapid expansion since then in solar PV and given Scotland's vast natural capacity for wind, there is distinct potential for this inequality to have grown considerably.

The Scottish Government also collects highly localised data on poverty and multiple deprivation, providing an opportunity to understand this relationship in more depth at a high resolution. Two key datasets were thus combined for the analysis: the Scottish Indices of Multiple Deprivation (SIMD) and OFGEM feed-in-tariff registration information.

4.1. Scottish Indices of Multiple Deprivation

The SIMD data is collected by the Scottish government every 4 years and includes 38 indicators of deprivation across 7 categories of income, employment, health, education, crime, housing and access to services (Scottish Government, 2020). This data is divided into 6976 data-zones: small-scale areas of 500–1000 people, which then fit into electoral wards (3–5000 people) and local council areas. Prominent differences exist across local authority areas in particular: different councils can differ starkly in their geographic and demographic make-up, bureaucratic process, executive and council partisanship and available funding. To account for these unobserved differences, mixed effects were applied with the piecewise SEM model using random intercepts on local authority areas. Random intercepts were opted for to allow the baseline of the model to vary across local authority areas and account for unobserved differences: because it is not anticipated that this variance between local authority areas will be uniform, random intercepts allow for a summary of the effect rather than an average effect that risks being biased in a fixed effects model. This was finally deemed appropriate with a Hausman Test. Four waves of the SIMD were combined for use in this analysis: 2009 – the year before the feed-in-tariff was introduced, 2012, 2016 and 2020 – the most recent year available.

4.2. Feed-in-tariff registration data

Feed-in-tariff data was collected from OFGEM Feed-in-Tariff registrations. Data was scraped using Python from a Renewable Energy Foundation (2020) database, which has information on all FiT-registered small-scale renewable energy systems below 5 MW in the UK. This information includes post code, size of installation, type of technology, ownership (domestic, community, industrial, commercial), parliamentary constituency and *local super output area* (LSOA), which corresponds to SIMD data zones in the case of Scotland. According to Scottish government figures, as of June 2019, there was approximately 731 MW installed feed-in-tariff capacity in Scotland (Energy Saving Trust, 2020). The feed-in-tariff data accounts for 727.4 MW, or 99.9% of that in total. Capacity was aggregated first by installation date to correspond with the waves of the SIMD. Installations pre-2009 were matched to the 2009 wave of the SIMD; capacity installed between 2009 and 2012 were matched with the 2012 wave; installations between 2012 and 2016 were matched with the 2016 wave; and all installations post-2016 were included as 2020. Capacity was then aggregated and merged with the SIMD by data-zone. To give a better idea of how the data is combined and the distribution of FiT capacity in Scotland, installed capacity (kW) by data-zone across Scotland is mapped in Fig. 2.

4.3. Included variables

4.3.1. New capacity added

The key dependent variable is a binary response indicating whether or not new domestic energy capacity was added within a data-zone at a given time point. This was chosen predominantly because it is not anticipated that the relationship between previous and future levels of capacity are strictly linear. Due to the relatively small number of people within data-zones themselves, the amount of capacity that can realistically be added as time goes on naturally decays. A binary variable where 1 = new capacity added and 0 = no new capacity was thus created as a more consistent indicator across all time points.

4.3.2. Income deprivation

The second key variable within the model is level of income deprivation within a data-zone, which is measured in the SIMD as the proportion of people within a data-zone claiming state benefits, ranging from 0 to 60\% of the data-zone population. Income deprivation is selected as the main independent variable for two reasons. First, actual income is not available consistently in Scottish data at this resolution and so income deprivation is the most meaningful measure available. Second and more fundamentally, because income deprivation is specified within the SIMD as the proportion of people within a given data-zone claiming non-pension state benefits, it more closely corresponds with poverty and other measures of deprivation than purely income

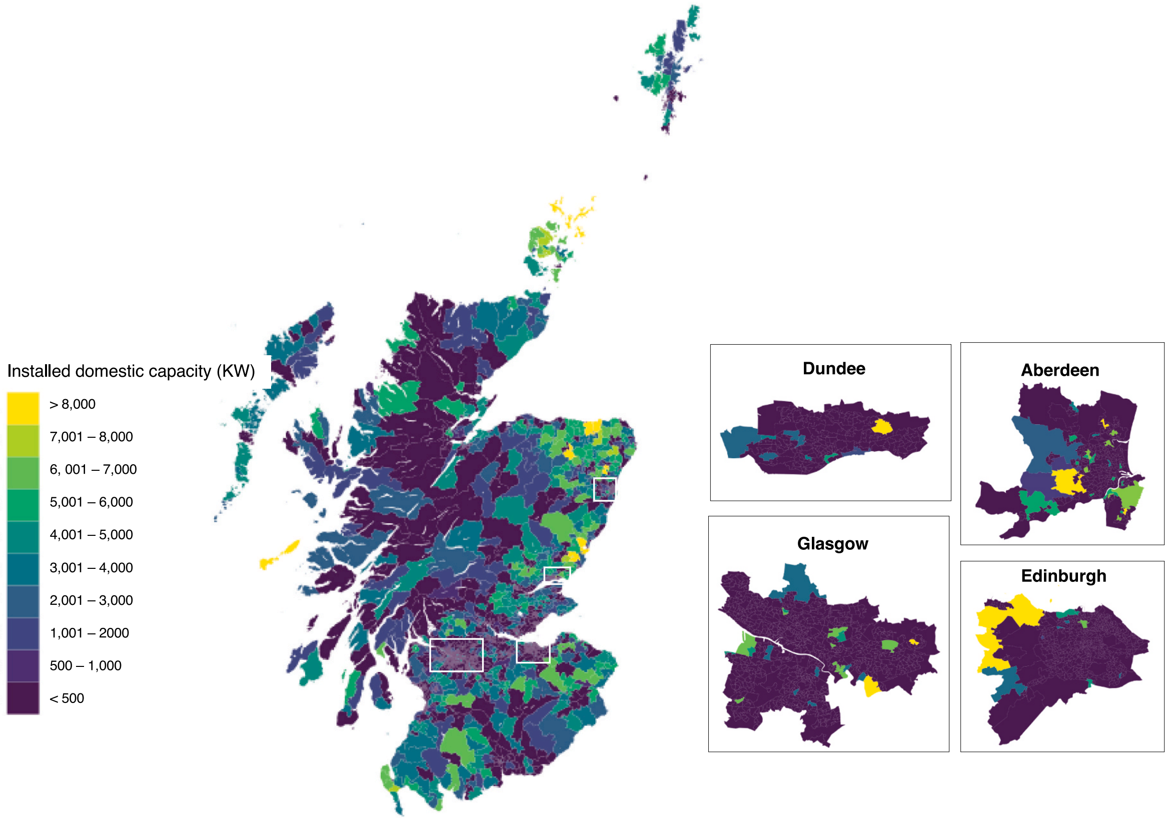

Fig. 2. Installed domestic FiT capacity in Scotland by SIMD data-zone.

alone, meaning that the social impacts outlined in the literature review (rather than solely financial aspects) are also somewhat accounted for. Through preliminary data exploration, variance inflation factors showed income deprivation to absorb a vast majority of the impacts of other theoretically interesting deprivation measures. Control variables typically are not included within structural equation models. This is the case here.

4.4. Written equations

The basic component equations from the feed-in-tariff trap model with the inclusion of random intercepts on local authority areas are specified as follows. The first equation is a generalized linear mixed effects model, where new capacity installed is the key binary dependent variable. The second equation is a linear mixed effects regression where income deprivation is a contin-uous linear output. PiecewiseSEM has no issue handling both logistic and linear regression within the same model framework.

$$install_{ij,t} = \beta income_{ij,t} + \beta install_{ij,t-1} + u_j + \varepsilon_{ij} \tag{1}$$

Where

$$income_{ij,t} = \beta income_{ij,t-1} + u_j + \varepsilon_{ij} \tag{2}$$

Equation (1), then, uses new installed capacity as the output variable. In this equation, $install_{ij,t}$ is a binary variable indicating whether or not new capacity was added within a data-zone i at time t; $\beta income_{ij,t}$ is the coefficient on level of income deprivation within a data-zone at time t; $\beta install_{ij,t-1}$ is the coefficient on whether or not a data-zone had new installed capacity at the previous time point to capture peer diffusion; uj is the random intercept for local authority area j; and ε_{ij} are finally the level-1 residuals, which are assumed to be normally distributed.

Equation (2) is then a linear mixed effects regression with the same basic overview, only with income deprivation as the main dependent variable, and income deprivation at the previous time point as the key predictor. These models were tested independently as mixed effect regressions using the lme4 package., before testing for the full theoretical model when pieced together within the feed-tariff-trap framework. Piecewise SEM analysis was conducted using the piecewiseSEM package in R (Lefcheck, 2019).

5. Results

5.1. Descriptive statistics

Basic descriptive statistics in Fig. 5 give a picture of the distribution of installed capacity in Scotland, broken down by technology and deprivation groups as of 2020. Within the SIMD, data-zones are ranked on their overall deprivation level, which is determined by the combination of all 38 measures from within the SIMD. This deprivation rank is divided into deciles for visualization.

Fig. 3 thus shows a substantial disparity across deprivation deciles for both solar PV (left) and wind systems (right), with installed capacity concentrated heavily in medium-high income groups. In both cases, the very lowest income groups lag significantly behind, revealing a fairly stark inequality as anticipated. Also interesting from these descriptive statistics is that the share of installed capacity appears to tail off at the upper-middle groups, which is consistent with previous analyses (Grover and Daniels, 2017; Lukanov and Krieger, 2019). This could be for a number of reasons. Given that household wind and solar are often cited as something that could potentially save on energy costs, it may be that those in the more affluent brackets have a less urgent need. It may also be a question of values, although this is not addressed here.

Fig. 4 then presents the growth in total feed-in-tariff installations across each wave of the SIMD, demonstrating how this inequality has expanded over time. As is to be expected, there is a considerable spike in the growth of FiT installations in the 2012 wave immediately after feed-

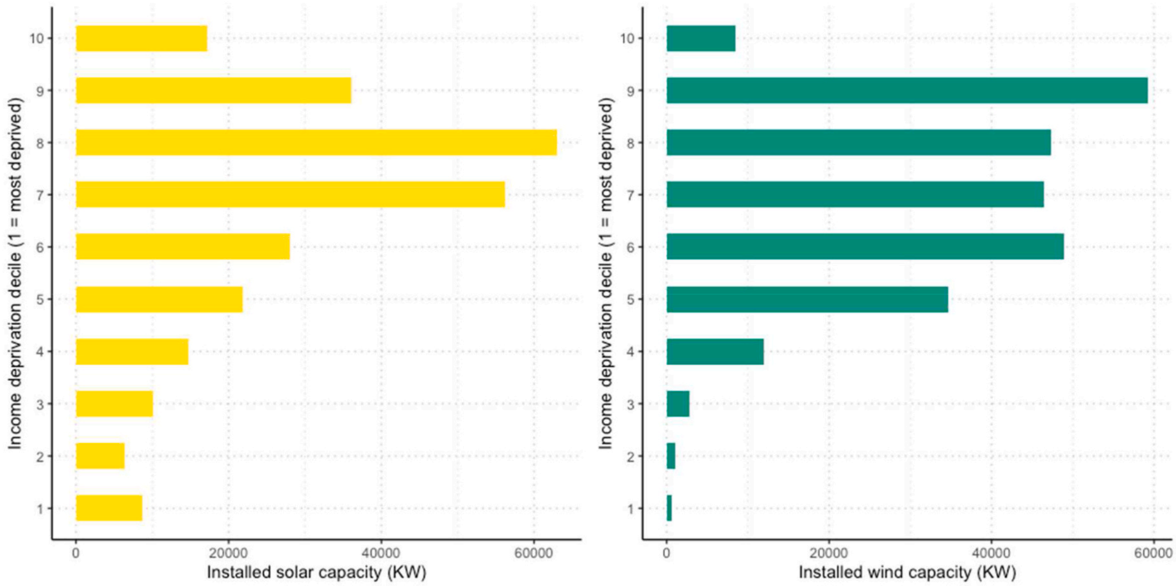

Fig. 3. Installed domestic FiT capacity by deprivation decile.

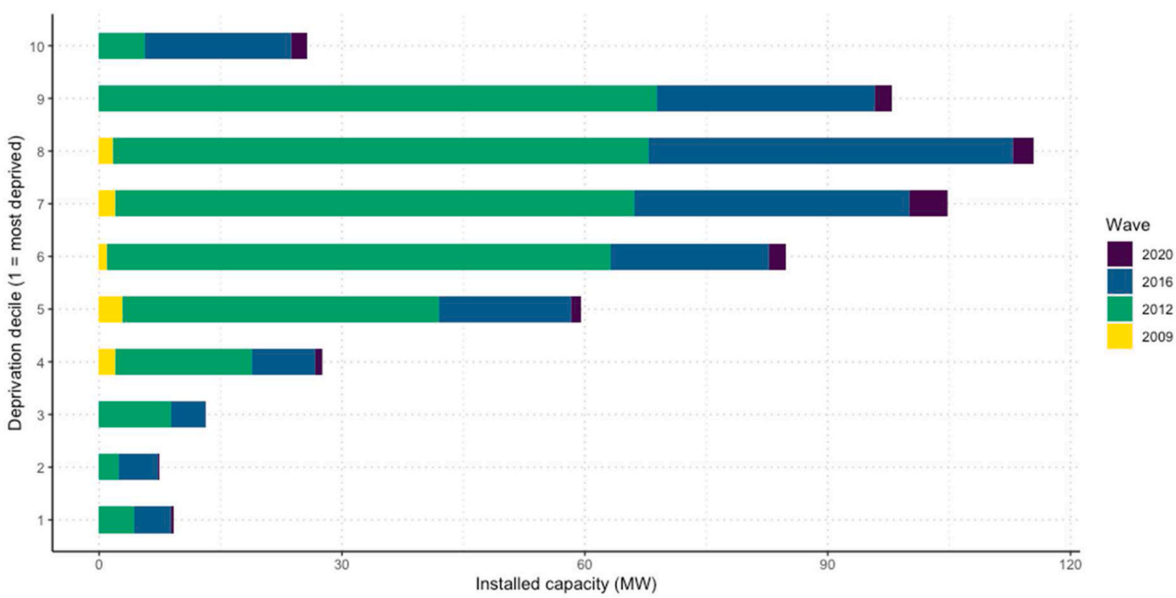

Fig. 4. MW feed-in-tariff capacity by SIMD wave.

in-tariff rollout in 2010. While this is the biggest growth spurt of new installations, between 2012 and 2016 growth is also considerable, particularly in the higher middle groups 7 and 8. Between 2016 and 2020, the number of new installations then tail-off considerably as the policy was wound to a close.

Table 1 finally shows the results of a basic generalized linear mixed effects logistic regression with new capacity installed as the dependent variable. For this analysis, random effects were also added on data-zone to account for there being repeated observations, and on year to account for the decay in uptake over time. From this table, two things are clear. First, the R^2 (variance explained within the model) is increased substantially with the inclusion of mixed effects on both data-zones and across local council areas. This suggests that differences in local council areas are substantial and so accounting for these with mixed effects is justified. Other model specifications were tested for robustness (no local council effects, solar and wind only) and outputs are given in Appendix A. The relationship holds across all analyses, with the mixed effects

Table 1
Mixed effects regression.

Predictors	New installed capacity
	Log-Odds
(Intercept)	−3.573***
Income deprivation	−0.597 ***
KW capacity$_{t-1}$	0.563 ***
Random Effects	
σ^2	3.29
τ_{00} Data Zone	0.86
τ_{00} Council area	1.17
τ_{00} year	1.07
Observations	20922
Marginal R^2 /Conditional R^2	0.044/0.253

*$p < 0.05$ **$p < 0.01$ ***$p < 0.001$.

model showing the strongest fit.

Second, the mixed effects regression output demonstrates that each of the key independent variables – income deprivation and lagged installed capacity – are statistically significant. This lends tentative support to H1 and H2, showing that higher levels of income deprivation reduce the likelihood of a new system being installed under the feed-in-tariff (H1), and that capacity being installed in an area already increases the likelihood (H2), both significant at the $p < 0.005$ level. While independently significant, however, what this model does not demonstrate is how these factors link together over time within the feed-in-tariff trap model. For this, we turn to the output of the piecewise SEM.

5.2. Structural equation model

The piecewise SEM model was specified using the hypotheses and path diagram given in Fig. 1. Accepted model fit measures for piecewise SEM are Fisher's C, which gives local estimation for piecewise SEM equivalent to chi-squared (χ^2), and the Root Mean Squared Error of Approximation (RMSEA) (Lefcheck, 2016a; Shipley, 2016). In the case of χ^2 and equivalents such as Fisher's C for assessing model fit, a p-value of >0.05 (rather than <0.05 as is typically the case with p-values) indicates a good model fit, with a higher p-value generally desirable. For RMSEA, the thresholds are <0.08 for an adequate model fit and <0.05 for a good model fit. In the model presented, the p-value on Fisher's C is 0.397 (>0.05) with a RMSEA of 0.011, indicating that the model is a good fit overall.

Fig. 5 gives the full output of the structural equation model. On the left of the figure, the greyed out sections represent the 2009 wave of the SIMD before the feed-in-tariff came into play in 2010, represented by the dotted vertical line. *KW_12* is then the 2012 wave of the SIMD, which is the first wave after the feed-in-tariff came into play. This has been labelled the "early adopter" wave to reflect. Standardized estimates rather than unstandardized coefficients are provided to allow us to better compare the magnitude of the effects of each independent variable.

From these estimates, there is considerable support for the feed-in-tariff trap. As anticipated, levels of income deprivation are consistently significant determinants of the likelihood of new installations (although somewhat less so prior to FiT rollout), with data-zones with high levels of income deprivation being less likely to access the feed-in-tariff than less deprived groups at all time points, lending support to H1. Installed capacity at $t-1$ is then a strong indicator of the likelihood of adding new capacity at t, significant at the $p < 0.001$ level for each of the included waves of data. This is true also of deprivation, with model coefficients suggesting that previous levels of income deprivation are a very strong indicator of future levels, lending support to H2 and H3 respectively.

In terms of the magnitude of these effects, some relationships and time periods have stronger impacts than others. Of these significant causal relationships, the impact of income deprivation on the likelihood of installation of new capacity within a given data-zone is consistent across each time period, ranging from −0.25 to −0.39 respectively, showing that areas with higher levels of income deprivation are significantly less likely to have household systems installed under the feed-in-tariff than higher income, lower deprivation areas. The relationship between previously installed capacity on the likelihood of a new installation is also strongly significant, particularly between 2012 > 2016: for this time period, peer diffusion was an even stronger predictor than income deprivation (−0.25 vs. 0.32 respectively). Comparatively, the peer effect from 2016 > 2020 is then smaller, although still positive and significant.

Beyond the direct relationships between immediately prior time points, the analysis also revealed significant effects from previous time points as represented by the dotted lines. Accounting for these effects is important since peer effects may not necessarily be tied exclusively to capacity installed at the immediately previous time point. In the case of installed capacity, significant links were drawn from 2012 > 2016 and 2012 > 2020. Perhaps surprisingly, it is actually the case that installed capacity in 2012 has a stronger effect on the likelihood of new capacity in 2020 than installed capacity in 2016. That is, installed capacity in a data-zone by the *early adopters* in the years immediately after the feed-in-tariff was first introduced had a strong direct effect on the likelihood of installations in both 2016 and 2020. While there is some minor effect between the pre-FiT 2009 wave and installations among early adopters, the strongest modelled peer effects stem from this early adopter wave. This suggests that peer diffusion is most prominent in

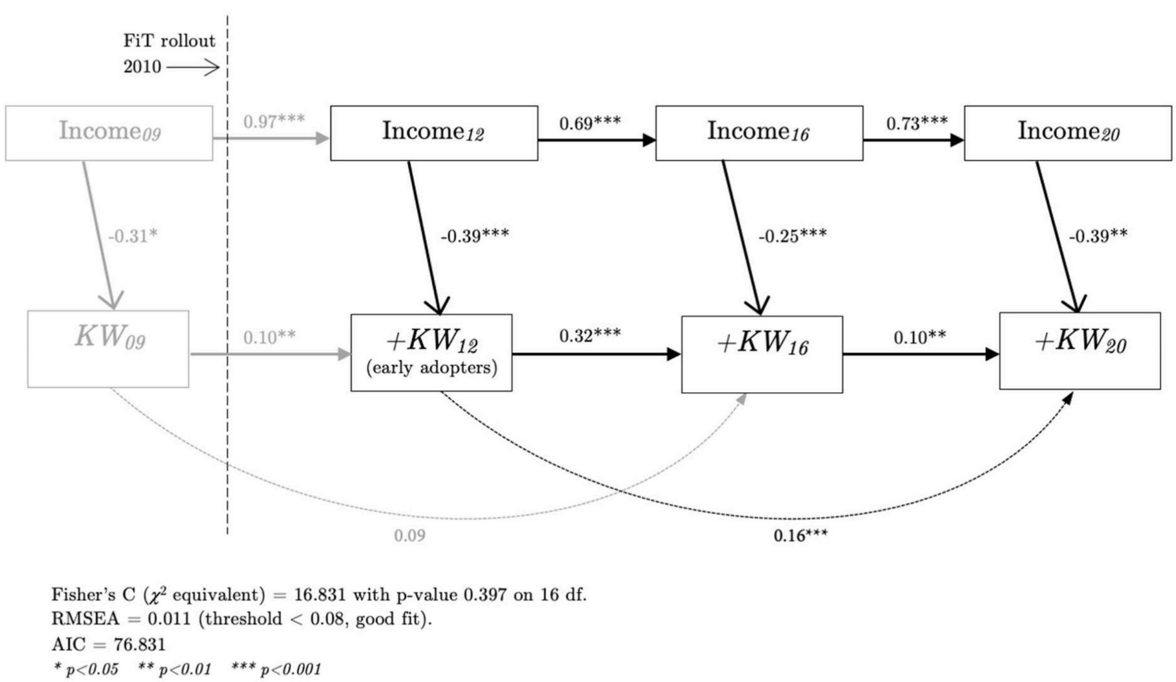

Fig. 5. Output of piecewise structural equation model.

those data-zones with high levels of early adoption.

Finally, Table 2 shows the R^2 of each response variable within the model; that is, the amount of variance in each response variable explained by the predictor variables. Marginal R^2 gives the variance in each variable explained before mixed effects are included, while conditional R^2 includes the variance explained with full mixed effects applied. From these results, then, we can see that a significant amount of variance in the response variables are again accounted for within the model. In the case of new capacity being added, deprivation levels and previously installed capacity accounts for an average of 23% of variance within the data, ranging from 11% in 2020 to as high as 35% in 2016. These numbers are significantly higher than the respective marginal R^2 figures (KW_{12} jumps from 0.07 to 0.23 with the inclusion of mixed effects, for instance), showing that local council areas do account for considerable variance within the data.

More compellingly explained within the model, however, are levels of income deprivation, which are almost exclusively explained by deprivation levels at the previous time point. At its highest, income deprivation in 2016 explains an enormous 95% of the variance in deprivation levels in 2020; the lowest figure here from Table 1 is still as high as 87%, demonstrating that levels of deprivation are stubborn and consistent over time. This finding lends robust support to H3.

6. Discussion

This analysis provides strong evidence for the existence of an inequality trap in the distribution of FiT installations in Scotland that is consistent over time. Inequalities exist and have widened in the adoption of household-level energy system along lines of deprivation, with more income-deprived communities significantly less likely to adopt than areas with lower levels of income deprivation across all timepoints. In addition to this, however, peer effects also appear to be significant and robust across each time period, suggesting that diffusion within data-zones themselves is a strong mechanism in influencing adoption. Critically, income deprivation is a strong indicator of adoption in 2012 immediately after the feed-in-tariff was first introduced, which then has strong peer effects at both 2016 and 2020, showing that the inequalities that emerged in the immediate years after the feed-in-tariff was introduced have been repeating over time, particularly through heightened influence of early adopters. Combined within the structural equation model, these results suggest that a combination of deprivation levels and peer effects have contributed to widening the gap in FiT access across socioeconomic groups in Scotland. These results thus point to inequalities in access to small-scale energy systems being more than simply a static function of socioeconomic circumstance alone. Rather, income deprivation affects the likelihood of adoption, which in turn plants the seed for peer diffusion to take place and lock in those socioeconomic inequalities over time.

Worth noting finally is something that the SEM model output here does *not* show, which is the impact of installed capacity on income deprivation. This relationship was tested but produced inconsistent and spurious model fit results, suggesting that the relationship is not statistically significant. For the feed-in-tariff trap this is significant, however. Because installed capacity does not significantly shift the dial on income deprivation within data-zones, and because income deprivation is so temporally stubborn, this suggests that even in data-zones with high levels of installed capacity, those experiencing income deprivation are not benefitting directly. This potentially signals a dual inequality gap: (1) between deprived and less-deprived data-zones, and (2) between deprived and less-deprived households *within* data-zones as well. Because actual income levels are not available at this level in Scotland over time, this within data-zone inequality cannot be accounted for, although it is broadly supported in findings from household-level studies in other contexts and locations (O'Shaughnessy et al., 2020).

Table 2
Variance explained by SEM model.

Response variable	Marginal R^2	Conditional R^2
KW_{12}	0.07	0.23
KW_{16}	0.09	0.35
KW_{20}	0.03	0.11
Income deprivation$_{12}$	0.94	0.94
Income deprivation$_{16}$	0.87	0.87
Income deprivation$_{20}$	0.94	0.95

6.1. Limitations

For these results, there are some elements missing from the analysis itself. First and most fundamentally, the proxy used to capture peer effects is just that: a proxy. While useful in lending support to the theorised causal relationships, more dedicated, widespread survey research is ultimately required to capture actual peer diffusion explicitly. Survey research which captures demographic, individual and political information, while not available in Scotland at this spatial resolution, can give a greater depth of understanding not just of the socioeconomic and demographic elements of communities but behavioural and individual information too, which will also have some part to play. Understanding diffusion beyond immediate geography (i.e. through social network analysis) or including the location of energy-related community organizations would also glean deeper insights into diffusion across different groups and communities.

Where this analysis considers household-level solar PV and wind adoption, it also omits discussion of other types of decentralised system, such as community energy projects, or other grant and loan schemes which may be theoretically less beholden to financial and informational barriers and as such better placed to bring benefit to lower income areas. Exploring this empirically would glean valuable comparable insights into a potential means for combatting this disparity. There is also a lack of connection made between the installation of small-scale energy under the feed-in-tariff and the impact this in turn has on income or deprivation measures. Given that commonly cited benefits of household-level energy include savings on fuel bills, and given that these inequalities clearly exist, there is a genuine concern that small-scale energy may also make pre-existing income and deprivation inequalities worse. Where results here demonstrate the existence of a "feed-in-tariff trap" effect, then, how this inequality then affects socioeconomic inequalities requires further robust exploration.

7. Conclusions and policy implications

These findings have stark implications for energy justice scholars and policymakers concerned with the just transition more broadly. Given the alleged socioeconomic benefits of household-level low-carbon technologies, the "feed-in-tariff trap" effect uncovers a potential for inequalities not only to emerge as a result of low-carbon technology grant and subsidy initiatives, but for existing socioeconomic inequalities to be further exacerbated as benefits are locked into clusters of higher income, early adopter groups. New injustices may arise as a result, or intergenerational injustices may be replicated as an unintended externality. While the feed-in-tariff undoubtedly helped to increase the use of clean energy technologies more generally then, its introduction also created a significant inequality issue, in part because it is a subsidy which relies on individuals opting-in to the scheme and navigating what can be very expensive, complex processes. Its winding down by the UK government now leaves the Scottish Government with an opportunity to design something more deliberately equitable.

To avoid the trappings of the feed-in-tariff in future, then, policymakers first need to remain mindful that opt-in schemes designed to incentivise low-carbon behaviours and technologies have implications not just for those who access them or for wider climate goals, but for those who cannot, and so understanding the social elements of those inequalities is crucial for a fair and effective distribution of benefits. That is not to say that such initiatives should be delayed or eliminated altogether – the environmental and social benefits for users are still hugely positive – but that a "just" transition will require more targeted support, particularly for lower-income groups, as opposed to relying solely on individuals to engage the process themselves. This is applicable not just to subsidies that require up-front investment but for initiatives such as the now-defunct UK government Green Homes Grant (UK Government2020b), which briefly provided funding for households looking to make their homes more energy efficient. Although the Green Homes Grant had in-built priority for lower-income households, for this priority to prove meaningful, ensuring that those households are aware of the policy and equipped to navigate the process in the first place is paramount.

Dedicated efforts to engage those households and make the process as straightforward as possible will thus be key to sharing the benefits of net zero under this type of opt-in grant or subsidy initiative. In Scotland, an expansion of the current Community and Renewable Energy Scheme to include a dedicated service for supporting low-income households in accessing various available grants and subsidies could be an effective way to leverage existing infrastructure and expertise. Limited Scottish and UK Government funding is available for local community groups to provide energy-related advice and guidance, although this is extremely competitive and often relies on volunteers or already-stretched citizen's advice services to sustain. Funding enough to let advice and advocacy outfits professionalise on a larger scale with more visible promotion, either in partnership or outwith the existing CARES programme, could lead to more effective local targeting of initiatives via people with strong local connections. By creating a dedicated outreach and advice service, the double disadvantage of income and informational barriers can be more effectively overcome.

Expansion of recent efforts by local authorities and intermediaries to coordinate retrofit and low-carbon technology schemes in social housing (iPower, 2020) may also provide an innovative jolt to kickstart this transition for groups who would typically be excluded (local authority-led branches of the Green Homes Grant tentatively had some more redistributive success). Policy and regulation which incentivises investment in affordable, low-carbon housing may help to limit the need for lower-income groups to "opt-in" to subsidies at all. In the absence of a feed-in-tariff at the UK government-level then, ambitious incentives from the devolved Scottish and local authorities will be crucial to ensure that any transition is not only "just", but that the transition can happen on the scale required.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Regression model robustness checks

Predictors	Install (no local council)	Solar (Mixed effects)	Wind (Mixed effects)
	Log-Odds	Log-Odds	Log-Odds
(Intercept)	−3.69 ***	−3.90 ***	−4.06 ***
Income deprivation	−0.43 ***	−0.42 ***	−0.71 ***
KW capacity$_{t-1}$	−1.29 ***		
Solar KW capacity $_{t-1}$		0.60 ***	
Wind KW capacity $_{t-1}$			0.26 ***
Random Effects			
σ^2	3.29	3.29	3.29
τ_{00}	0.96 $_{\text{Data\_Zone}}$	0.96 $_{\text{Data\_Zone}}$	0.96 $_{\text{Data\_Zone}}$
	1.05 $_{\text{year}}$	1.05 $_{\text{year}}$	1.05 $_{\text{year}}$
		0.57 $_{\text{Council\_area}}$	3.08 $_{\text{Council\_area}}$
ICC	0.37	0.32	0.51
N	6976 $_{\text{Data\_Zone}}$	32 $_{\text{Council\_area}}$	32 $_{\text{Council\_area}}$
	3 $_{\text{year}}$	3 $_{\text{year}}$	3 $_{\text{year}}$
		6976 $_{\text{Data\_Zone}}$	6976 $_{\text{Data\_Zone}}$
Observations	20922	20922	20922
Marginal R^2 /Conditional R^2	0.050/0.106	0.033/0.209	0.066/0.382

*$p < 0.05$ **$p < 0.01$ ***$p < 0.001$.

Appendix B. AIC scores

Model 1 (model included in paper)	5937.8
Model 2 (no local council effect)	6445.8

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