Energy Economics 143 (2025) 108244

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Socioeconomic inequality in low-carbon technology adoption

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ARTICLE INFO

JEL codes:
L94
Q42
Q55
P46
O33

Keywords:
Technology adoption
Inequality
Low carbon technologies
Renewable resources

ABSTRACT

The widespread adoption of low-carbon technologies (LCTs) by residential consumers is a cornerstone of net zero targets worldwide; however, LCT adoption may not be equally distributed across socioeconomic groups. Our paper contributes to the related literature by exploring socioeconomic inequality in LCT adoption and its underlying sources. We exploit nationally representative longitudinal data on the adoption of three key LCTs (solar photovoltaics, solar water heating, and electric vehicles) in the UK. We investigate the aggregate role of predetermined socioeconomic factors in determining socioeconomic inequalities in LCT adoption. We further contribute to the literature by employing Shapley-decomposition techniques to reveal the relative contribution of each individual socioeconomic factor to the total estimated socioeconomic inequality. Our results suggest that socioeconomic inequalities in LCT adoption have fallen over the last decade but remain prevalent, non-negligible in magnitude and highly statistically significant. Our analysis of longitudinal LCT adoption patterns shows that those consumers who have recently adopted LCTs, are contributing to the reduction in the observed socioeconomic inequalities over time. Policies targeting groups with the most disadvantaged socioeconomic background are crucial in order to mitigate the observed inequalities, potentially hindering a more rapid low-carbon transition.

1. Introduction

The adoption of low-carbon technologies (LCTs) by residential consumers is central to the UK's legally binding commitment to achieving net zero by 2050. It is difficult to overstate the role of consumers, as their potential adoption of LCTs, such as electric vehicles and solar panels, would represent nearly half (47 %) of the UK's 2035 abatement target for the power sector (Committee on Climate Change (CCC), 2022). It is clear therefore that decarbonisation in the automotive and housing sectors is paramount for the success of the low-carbon transition.[1] Indeed, according to the Climate Change Committee (Committee on Climate Change (CCC), 2022), surface transport and buildings contributed 43 % of the UK's emissions in 2021. Despite these sectors being the UK's two largest sources of emissions, there are positive signs that *some* consumers have increasingly embraced more sustainable ways to live and travel.

Whilst consumer adoption has been identified as a driver in the development of eco-innovations (Kesidou and Demirel, 2018), making environmentally sustainable choices is subject to financial and technological constraints, which are encountered to different extents across society. The evidence from the United States, and California in particular, where the adoption of LCTs has been relatively rapid thanks to the subsidies of the State's Government, reveals that ownership of LCTs is more prevalent among high-income households (Borenstein and Davis, 2016; Barbose et al., 2022); this may lead to questioning the equity of such subsidies (Borenstein et al., 2021). The present paper aims to bridge a gap in the literature by exploring socioeconomic inequality in LCT adoption and its underlying sources.

Since 2010, the cost of installing domestic solar panels in the UK has decreased by 60 % (Department for Business Energy and Industrial Strategy (BEIS), 2021). Even though the UK's flagship subsidy scheme ended in 2019, the cumulative number of installations broke the 1 million threshold and has achieved a similar capacity to that of some nuclear power stations (MCS, 2022). The continued strength of the

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[1] It is important to note that the UK Government's Heat and Buildings Strategy (HM Government, 2021a) endorses a target of 600,000 yearly heat pump installations up to 2028, but this target is perceived as unlikely to be achieved, e.g., see House of Lords Environment and Climate Change Committee (HM Government, 2023a).

https://doi.org/10.1016/j.eneco.2025.108244
Received 3 June 2024; Received in revised form 15 January 2025; Accepted 24 January 2025
Available online 27 January 2025

unsubsidised demand for residential solar panels is perhaps unsurprising as consumers were able to achieve significant levels of savings in the face of a rapid rise in wholesale energy prices during 2021 and 2022 (HM Government, 2023b).

All the while, the electric vehicle (EV) market gained traction. In 2021, fully electric vehicles (EV) and plug-in hybrids (PHEV) made up 12 % and 7 % of all new vehicles sold in the UK respectively (Committee on Climate Change (CCC), 2022). As of today, the UK has around 250,000 EVs on its roads and is expected to reach 10 million by 2030 (Office for Gas and Electricity Markets (OFGEM), 2023), which is consistent with the UK's ban on all new petrol and diesel vehicles by 2030. Yet, alongside increasing annual costs of EV charging, potential adopters will also focus on the upfront cost of EVs, which is only expected to reach parity with similar-sized petrol or diesel engines later this decade (HM Government, 2023c).

A few studies have explored the presence of socioeconomic inequality in the diffusion of LCTs. Barbose et al. (2022) provide insights into how inequality may influence solar technology adoption by mapping the heterogeneous socioeconomic and demographic trends across regions and time in the United States (US). They find that residential solar adoption appears favoured by white, highly educated, and high-income households working in the professional or business/financial sectors; however, the authors argue that these disparities have been slowly reducing in recent years. Likewise, solar panel installations appeared unequally distributed in the population by age, gender, education and, ethnicity (see Sunter et al., 2019; Sovacool et al., 2022) while similar socioeconomic factors matter for EV adoption according to Axsen and Sovacool (2019), Qiao and Dowell (2022) and Sovacool et al. (2022). Steadman et al. (2023) investigate local factors in the adoption of solar PV in the UK. They identify the significant role of community PV installation and the presence of newly built dwellings in the pattern of adoption. They also find evidence of clusters of high adoption in specific regions of the country, potentially related to local economic conditions. More broadly, recent research established positive effects of education on pro-climate outcomes, which include attitudes towards renewable energy and energy efficiency, although the authors do not focus explicitly on the adoption of specific LCTs (Angrist et al., 2023). By investigating early-life educational attainment, Angrist et al. (2023) capture the effect of education on climate change outcomes (including energy efficiency behaviours and renewable energy attitudes), as well as the role of socioeconomic position in later life and other mediators, associated with an exogenous increase in schooling.

Other scholars have suggested that the role of education, gender and ethnicity may be only weakly associated with solar panel uptake (Best et al., 2023). Much more limited is the work on the association between childhood socioeconomic status (SES) and LCTs, which focuses on developing countries and cleaner domestic fuel use (Mussida and Sciulli, 2022). Despite the lack of evidence on the association between parental SES and LCT adoption, parents have been found to influence the energy literacy (Pearce et al., 2020), environmental attitudes and energy-saving behaviour of their children (Karatepe et al., 2012; Fell and Chiu, 2014).

Overall, the presence of socioeconomic inequalities in LCT adoption is understudied, with most of the existing literature focusing on specific disparities involving certain socioeconomic characteristics, often relying on non- representative samples and on *reported* LCT-related behaviours rather than *actual* purchases or installations (e.g., Alipour et al., 2020; Barbose et al., 2022; Best et al., 2023; Sunter et al., 2019). In this study, we aim to contribute to the literature by providing evidence of the evolution of socioeconomic inequality in LCT adoption over time, using nationally representative UK longitudinal data. Examining socioeconomic inequalities in LCT adoption in the UK—a country responsible for the fifth-largest per capita contributions to climate change (Committee on Climate Change (CCC), 2019)—has significant policy implications for the low-carbon transition.

There is a dearth of evidence not only on inequality in LCT adoption but also on which members of society have been at a disadvantage to adopt, as argued by scholars of the "just transition" to a low-carbon future (Carley and Konisky, 2020). Our analysis provides novel evidence on how early-life circumstances could directly and indirectly influence the adoption of LCTs, and, thereby, identify "sections of society" that may have been hitherto overlooked in the processes aimed at promoting the energy transition (Jenkins et al., 2021).

Our paper contributes to the literature in a number of ways. First, we exploit the availability of nationally representative longitudinal data for the UK to explore the evolution in the adoption of three key LCTs (solar photovoltaics, solar water heating, and electric vehicles) in light of their cost reductions and of the increasing consumer awareness of their merits (Committee on Climate Change (CCC), 2022).

Second, we explore the aggregate role of observed socioeconomic characteristics in determining socioeconomic inequalities in LCT adoption, as opposed to focusing on disparities in adoption due to a specific socio-demographic factor. Relying on the inequality of opportunity (IOp) approach (e.g., Roemer, 1998, 2002; Bourguignon et al., 2007; Ferreira and Gignoux, 2011), we employ factors that are economically exogenous to a large extent and beyond an individual's control, which include family background (labelled as socioeconomic circumstances in the IOp framework). Focusing on predetermined circumstance variables, such as parental socioeconomic background, may alleviate endogeneity concerns in our analysis. Exploring later-life socioeconomic factors, such as housing tenure or income, is more likely to result in endogeneity issues. For example, it can be argued that tenure decisions may be determined by consumers' willingness and effort to improve their housing conditions, e.g. via the installation of LCTs for water heating and electricity; but at the same time the adoption of these LCTs may be determined by housing tenure given the limited agency of tenants to install home improving technologies.

The IOp framework is based on a broad inequality concept but focuses specifically on disentangling inequalities due to predetermined circumstances, such as parental socioeconomic background. Aside from alleviating endogeneity concerns, this approach is of particular interest from a normative point of view — normative views often suggest that government policies need not aim to eliminate all outcome inequalities but may be justified in seeking to reduce those that arise from unequal, predetermined opportunities. It is often argued that inequalities due to factors beyond an individual's responsibility are inequitable, and should be compensated by society (Peragine, 2004). Specifically, within the context of socioeconomic inequality in LCT adoption, the IOp framework allows us to explore factors which are beyond an individual's control, and which create disadvantages when adopting LCTs. For example, if disparities in LCT adoption which can be attributed to a disadvantaged parental background were identified this may point to potential benefits of policy interventions targeting vulnerable families with adolescents and young children. The extent to which these early life disadvantages can influence the LTC adoption behaviour of these children and adolescents in later life, and thus affect the general level of LCT adoption, is of particular interest. On the other hand, disparities in LCT adoption that are solely and directly attributed to effort (such as motivation patterns and efforts to gather information) may be regarded as more legitimate sources of the observed inequalities in LCTs. In this study, by utilising an inequality framework and employing predetermined socioeconomic characteristics, we are able to explore the total role of predetermined socioeconomic characteristics in determining current LCT inequalities, which includes their direct role in LCT adoption as well as their indirect role, to the extent that these predetermined characteristics partially affect later life's efforts related to LCT adoption.

Overall, we found systematic and relatively large socioeconomic inequality in LCTs that remained evident but reduced in magnitude over the last decade, during which an increase in the levels of LCT adoption was observed. We further contribute to the literature by employing Shapley-decomposition techniques to explore the relative contribution of each socioeconomic variable to the total estimated socioeconomic inequality.

We also tested our inequality results by restricting our sample to specific longitudinal sequences of LCT adoption. A comparison of the level of socioeconomic inequality between the subsample of those who persistently adopt/do-not-adopt LCTs (i.e., do not change their adoption pattern) with subsamples of those with transitory adoption patterns (to or from LCT adoption) gives us insights about what drives the observed reduction in socioeconomic inequality in LCTs over time, happening at a time of increasing LCT adoption. Overall, our results reveal that those following transitory LCT adoption patterns, and in particular those who have recently adopted LCTs, seem to be contributing to the recent reduction in the observed socioeconomic inequalities over the last decade.

The rest of the paper is organised as follows. Section 2 describes the methods and data used in our analysis. The results of our analysis are presented and discussed in Section 3 and Section 4 concludes.

2. Methodology and data

2.1. Measuring socioeconomic inequality in LCT adoption

We model LCT adoption as a function of socioeconomic circumstances, in line with the IOp framework (Roemer, 1998, 2002; Bourguignon et al., 2007; Ferreira and Gignoux, 2011). Specifically, we assume that LCT adoption is a function of: a) circumstances which are beyond individuals' control and b) effort factors for which individuals are partially responsible. Circumstance variables are assumed to be economically exogenous by definition, while "effort" variables can be affected by circumstances and other unobserved factors (v_i); therefore, each of our LCT adoption outcomes can be expressed as:

$$y_i = f(c_i, e(c_i, v_i), u_i) \tag{1}$$

where, y_i denotes the adoption of a specific LCT by individual (i). The vector c stands for the observed circumstances for each individual (i) that are assumed to affect LCT adoption, while e represents the effort variables. The decision to invest in energy and carbon-saving technologies is complex, and the time and effort required to make an optimal decision are costly (Allcott and Greenstone, 2017). Effort can influence underinvestment in even more salient ways particularly if one faces hassle – such as going through the seemingly cumbersome process of applying for eligible government support (Fowlie et al., 2015). The unobserved error term v_i captures random variations in effort that are independent of c, while u_i represents random variation on the LCT adoption, including measurement error which is independent of both c and e[2]; these unobserved error terms are often labelled as 'luck' in the literature (e.g., Lefranc and Trannoy, 2017).

In this study, we aim to measure overall socioeconomic inequality in LCT adoption which can be attributed to our set of circumstance variables, as a share of total inequality. This approach characterises socioeconomic equality as a situation where all individuals face the same opportunity set, prior to their effort and outcomes being realised; in other words, equality indicates no differences in the LCT adoption due to different (socioeconomic) circumstances. In this case, a reduced-form equation can be derived from Eq. (1), which does not require the inclusion of effort variables (e.g., Aaberge et al., 2011; Fleurbaey and Peragine, 2013; Davillas and Jones, 2021):

$$y_i^* = a + \beta c_i + \varepsilon_i \tag{2}$$

where, y_i^* stands for the relevant latent LCT outcome variable for our regression models,[3] and β represents the *total contribution* of circumstances that include both the direct influence of circumstances on LCT adoption, and the indirect effect of circumstances through efforts.[4] Specifically, this analysis implicitly assumes that the partial correlations between effort (e) and circumstances (c) should also be treated as a circumstance; this embodies the indirect effect of the circumstances on our LCT outcomes that is channelled through effort and (along with the direct role of circumstances) is reflected in our reduced form specification so that β (in Eq. (2)) captures both the direct and indirect contributions. For example, assuming that acquiring LCT literacy is a form of "effort" affecting an individual's adoption of solar panels, the potential influence of parental education (a key socioeconomic circumstance) that comes through the impact of parental education on an individual's LCT literacy should be also treated as a circumstance which affects LCT adoption.

Taking the predicted outcome from Eq. (2) ($\hat{y}$), the observed socioeconomic inequality in our LCT adoption can be estimated by applying a suitable inequality measure, I(.), to $\hat{y}$:

$$\theta_I = I(\hat{y}) \tag{3}$$

Given that the variation in vector $\hat{y}$ is exclusively due to circumstances, Eq. (3) refers to variations in LCT adoption outcomes attributed to socioeconomic variables reflecting the circumstances captured in our analysis. The choice of the inequality measure $I(.)$ depends on the type of the outcome variable being examined. Following Davillas and Jones (2021) and Chávez Juárez and Soloaga (2014), given the binary nature of our outcomes we employ a dissimilarity index. An estimator of the dissimilarity index (Fajardo-Gonzalez, 2016) can be given by:

$$I(.) = \frac{2}{n\overline{y}} \sum_{i=1}^{n} |\hat{y}_i - \overline{y}| \tag{4}$$

where, $\hat{y}_i = E(y_i|c_i)$ and $\overline{y} = E(\hat{y}_i)$. The dissimilarity index ranges from zero to one, with zero indicating full socioeconomic equality and one indicating full inequality. The index can be interpreted as the minimum fraction of the number of LCT adopters that need to be redistributed across socioeconomic groups to achieve equality (Fajardo-Gonzalez, 2016). It should be noted here that in the presence of unobserved circumstances not accounted for in Eq. (2), our measure of socioeconomic inequality in LCT adoption should be considered as the lower-bound estimate of overall socioeconomic inequality, i.e., the inequality due to *all* socioeconomic circumstances in LCT adoption, not only to those observed in our analysis (Ferreira and Gignoux, 2011).

Our set of LCT measures are obtained from Wave 4 (January 2012 – May 2014) and Wave 10 (January 2018 – May 2020) of Understanding Society – the UK Household Longitudinal Study (UKHLS) data. We estimate socioeconomic inequality in LCT adoption separately for each wave for a balanced sample (valid responses at both Wave 4 and 10), which allows us to compare the evolution in socioeconomic inequality as LCT adoption progresses over time.

In subsequent analysis, we capitalise on our longitudinal data to explore patterns of LCT adoption for the same individuals over time. We also estimate and compare socioeconomic inequality measures (based on Eqs. (2), (3) and (4)) by restricting the sample to persistent innovators and non-adopters (i.e., those who always report adoption or

[2] LCT adoption outcomes are the realisations of random processes; in our socioeconomic inequality analysis we are unable to assess whether the unexplained component of these outcomes is attributed to unobserved circumstances, unobserved effort, measurement error or pure chance. It should be explicitly noted that in this study we aim to measure the component of LCT adoption decisions attributed to the variables capturing observed circumstances.

[3] We adopt Probit models in our analysis but, as a sensitivity analysis, we also estimated equation 2 using Logit regression models obtaining almost identical results (details are provided in the Results section and the Appendix).

[4] Details on the derivation of the reduced form equation 2 from equation 1, a common practice in the relevant IOp literature, are available elsewhere (Bourguignon et al., 2007; Carrieri et al., 2020).

non-adoption of LCTs in Waves 4 and 10), and to sub-samples successively augmented by population groups that transition between adoption and non-adoption of LCTs between Wave 4 and 10. This analysis allows us to compare the level of socioeconomic inequality between those who persistently adopt/do-not-adopt LCTs over time (i.e., do not change their adoption patterns) and when including those who exhibit transitory adoption patterns. These comparisons may provide insights on whether those transitory adoption patterns drive the observed variations in socioeconomic inequality in LCT adoption over time (i.e., between Wave 4 and 10).

2.2. Decomposing the socioeconomic inequality in LCT adoption

Shapley-Shorrocks decomposition analysis is employed to measure the contribution of circumstances variables (c) to overall socioeconomic inequality (Shorrocks, 2013; Chávez Juárez and Soloaga, 2014; Davillas and Jones, 2021). The Shapley-Shorrocks decomposition is implemented by estimating inequality measures for all possible permutations of the socioeconomic variables in our analysis prior to calculating the average marginal effect of each socioeconomic variable on the overall socioeconomic inequality in LCT adoption. Typically, the contribution of each specific factor can be calculated by keeping all socioeconomic variables, but not the one of interest, constant or by only keeping the socioeconomic variable of interest constant and defining its contribution as a residual from the total inequality; either path is conceptually valid. Unlike other decomposition methods, the Shapley-Shorrocks averaging procedure allows a path-independent additive decomposition (Shorrocks, 2013; Chávez Juárez and Soloaga, 2014; Davillas and Jones, 2020). Moreover, the Shapley-Shorrocks decomposition is exactly additive as it can decompose socioeconomic inequality into positive, proportional contributions from individual covariates. The decomposition analysis is applied to the dissimilarity indices for the measurement of socioeconomic inequality in LCT adoption in Waves 4 and 10, as well as across our sub-sample analysis based on longitudinal patterns of LCT adoption.

2.3. Data

The data are obtained from Wave 4 (January 2012 – May 2014) and Wave 10 (January 2018 – May 2020) of UKHLS — a longitudinal, nationally representative UK survey (University of Essex, Institute for Social and Economic Research, 2022). Our study requires valid (individual-level) adoption measures for all three LCTs (solar photovoltaics, solar water heating, and electric vehicles) that are consistently measured across successive UKHLS waves. Given that questions regarding LCT adoption measures are administered only in selected UKHLS waves, the availability of data on the relevant LCT adoption measures (the outcome variables in this study) constrained our analysis to UKHLS Waves 4 and 10. Specifically, the survey questions used to measure the presence of any electric/hybrid vehicles were not collected until UKHLS Wave 4 (and, thus, we need to focus on UKHLS Wave 4 and beyond); within this range of UKHLS waves, solar photovoltaics and solar water heating measures are also available in UKHLS Waves 4 and 10.[5]

As we aim to measure and compare the evolution of the socioeconomic inequality in LCT adoption between UKHLS Wave 4 and 10, we restrict our main analysis to a balanced sample of respondents between the two waves; this allows us to compare the levels of socioeconomic inequality in LCT adoption at different times, as well as analyse subsamples with distinct longitudinal LCT adoption patterns. After excluding all missing cases in our LCT measures, and the circumstance variables included in our analysis, our final *balanced* sample contains 25,167 individuals in each wave (corresponding to 50,334 person-year observations for the two UKHLS waves).

Sample weights are used to ensure that our findings are representative of the UK population. The weights were calculated using backward stepwise logistic regressions on observed predictors, adjusting the published UKHLS sample weights to account for attrition between Waves 4 and 10 (given our balanced sample), item missingness and unit nonresponse for all variables used in our analysis.

2.4. Low-carbon technology (LCT) outcomes

Our set of outcome variables refers to three LCTs adopted by households: a) solar photovoltaics for electricity (*SOLARPV*) *installed* by households; b) solar water heating (*SOLARHEAT*) *installed* by households; and c) hybrid or electric vehicles (*HYBRIDEV*) *owned* or continuously used by households.

Specifically, the *SOLARPV* variable takes the value of one if the respondent's household has installed solar panels for electricity; and zero otherwise. Similarly, *SOLARHEAT* takes the value of one if the respondent's household has installed solar panels for the purpose of heating water and zero otherwise. It is important to note here that for both *SOLARPV* and *SOLARHEAT*, individuals from households who are unable to adopt these technologies due to living in rented accommodation, those who are considering but have not yet adopted these LCTs, and those who have not yet considered installing these technologies are coded as zero. Our third outcome variable *HYBRIDEV* takes the value of one if the respondent's household owns or has continuous use of either a hybrid (i.e., petrol and electric) or electric battery-operated vehicle (i.e., a car or van) and zero otherwise.

Table 1 provides the description of our set of LCT adoption variables along with their mean values separately for UKHLS Wave 4 and 10. Our results show an increase in those adopting solar panels for electricity and for water heating between Wave 4 and 10. Specifically, within six years, the proportion of individuals using solar panels for electricity generation more than doubled (from 3.0 % to 6.5 %); similarly, the proportion of respondents reporting solar water heating technology increased from 1.4 % in Wave 4 to 2.1 % in Wave 10. Table 1 also shows an increase in the proportion of our sample reporting at least one electric or hybrid-electric vehicle available at the household level — from less than 1 % in 2012–2014 (Wave 4) to 2.8 % in 2018–2020 (Wave 10), reflecting the

Table 1
Definitions and mean values – LCT outcomes.

		Wave 4	Wave 10
Variables	Definition	Mean	
SOLARPV	1 = Individual belongs to a household which has installed solar panels for electricity; 0 = otherwise or not applicable/living in rented accommodation.	0.030	0.065
SOLARHEAT	1 = Individual belongs to a household which has installed solar water heating; 0 = otherwise or not applicable/living in rented accommodation.	0.014	0.021
HYBRIDEV	1 = Individual belongs to a household which has at least one electric vehicle or hybrid-electric vehicle; 0 otherwise.	0.004	0.028

Note: Mean values are weighted using sample weights. Balanced sample of UKHLS Waves 4 and 10.

[5] Beyond data availability, the choice of which UKHLS waves to include in our analysis is also influenced by practical considerations. For example, plug-in or hybrid vehicles did not reach more than 1.5 % of the new vehicle registrations/purchases (and, thus, a much smaller share of the total number of all licensed vehicles in the UK) until after December 2013 (Society of Motor Manufacturers and Traders, 2015). Given that UKHLS Waves 1–3 were collected between January 2009 and July 2013, these UKHLS waves would not provide a sufficient sample size for conducting meaningful analysis on electric/hybrid vehicles, even if the data on such vehicles had been collected during these waves.

growing adoption of new low-emission vehicles.

2.5. Socioeconomic circumstances

All our socioeconomic variables are obtained from UKHLS Wave 4 (unless otherwise stated below) and are treated as time-invariant variables. The choice of our circumstance variables reflects factors regarded as sources of socioeconomic inequality in LCT adoption that are beyond an individual's control.[6] Limiting our inequality analysis to predetermined factors may help mitigate any endogeneity concerns; this also allows us to obtain the total contribution of these predetermined characteristics to the inequalities in LCT adoption, i.e., the contribution coming *directly* from predetermined circumstances, as well as from their *indirect* effects via later life factors (such as "efforts" and related potential mediators) which are also correlated with LCT adoption.

Birth cohort[7] and gender are included in our set of circumstances, as existing literature has shown systematic differences in low-carbon energy adoption patterns by gender and across birth cohorts (Day, 2015; Fraune, 2015; Berkeley et al., 2018; Petrova and Simcock, 2021; Han et al., 2022).[8] Ethnicity is also treated as a circumstance variable and defined as equal to one for white ethnicity and zero otherwise; it has been shown that those of minority ethnic backgrounds tend to have a lower rate of adoption of low carbon technologies in the United States, and even more so in low- and middle-income countries (Sovacool et al., 2022).

Socioeconomic status (SES) in childhood is regarded as an important source of inequality within the broad IOp framework (for example, Bourguignon et al., 2007; Ferreira and Gignoux, 2011). With respect to LCTs, although there is limited literature that directly assesses the effect of parental SES on LCT adoption, there is evidence that parents influence childhood energy literacy (Pearce et al., 2020), environmental attitudes and energy saving behaviour (Karatepe et al., 2012; Fell and Chiu, 2014), and the choice of heating fuel in young households established outside of the home (Mussida and Sciulli, 2022). For the purpose of our study, parental occupational status when the respondent was aged 14 is used to proxy childhood SES. Specifically, we employ one categorical variable for the mother's occupational status and one for the father's: not working, four occupation skill levels and a category for missing data.[9] Parental education is also employed as an additional indicator of childhood SES. A combined categorical variable for the highest parental education level is employed, given the high correlation between mother's and father's education (Kenkel et al., 2006); this is a four-category variable defined as: left school with no/some qualification, post-school qualification/certificate, degree, and a missing data category.

We include an individual's own education as a socioeconomic circumstance variable based on a normative assumption that the level of secondary schooling achieved by age 18 is highly influenced by parental and environmental factors during earlier life and, thus, is (at least partially) beyond an individual's responsibility (Davillas and Jones, 2020). Bar Gai et al. (2021) found education to be among the key barriers to solar adoption at the community level in the US; yet, in China, highly educated households were associated with EVs' but not with solar panels' uptake (Wen et al., 2023). Although they do not focus on the adoption of specific LCTs explicitly, Angrist et al. (2023) found a positive causal effect of education on pro-climate outcomes that include energy efficiency behaviours and attitudes towards renewable energy. The individual's own education is measured using a 5-category variable: no qualification, basic qualification, O-Level, A-Level/post-secondary and degree. Given that there is a small proportion of our sample still enrolled in education or who completed their degree between UKHLS Waves 4 and 10, the highest recorded educational attainment is used for the needs of our analysis. Summary statistics for all the socioeconomic variables used in our analysis can be found in Table A1 (Appendix).

It should be noted that although our set of socioeconomic circumstance variables is carefully selected to reflect predetermined circumstances, omitted unobserved circumstances may be a concern of potential bias. Even if this was the case, our socioeconomic inequality measures can be interpreted as the lower-bound estimates of the overall inequality due to all circumstances, not only those that are observed (Davillas and Jones, 2020).

3. Results

3.1. Socioeconomic inequality in LCT adoption and its evolution over time

Table 2 presents the dissimilarity indexes for our three LCT outcomes and their evolution over time (UKHLS Wave 4 vs Wave 10).[10] Overall, our results reveal systematic socioeconomic inequalities in the adoption of solar panels for electricity (*SOLARPV*), solar water heating (*SOLARHEAT*) and electric vehicle/hybrid-electric vehicle (*HYBRIDEV*), with highly statistically significant dissimilarity indexes for both UKHLS Waves 4 and 10. For example, the estimated dissimilarity index for low-carbon vehicle adoption for Wave 4 is 0.382. This dissimilarity index can be interpreted as the minimum fraction (about 38 %) of LCT adopters that need to be redistributed across socioeconomic groups to achieve socioeconomic equality in LCT adoption. Overall, our results show that the observed socioeconomic inequalities in LCT in Wave 4 are not only systematic but of non-negligible magnitude (with the relevant dissimilarity indexes ranging between 0.277 and 0.382 across LCT measures).

However, we also observe a reduction in the level of socioeconomic inequality over time across all three LCT measures (p-value<0.001 for the pairwise tests of differences in dissimilarity indexes between Wave 4 and 10, separately for each of the LCT measures); this may indicate that the increased LCT adoption over time (as evident in Table 1) has also

Table 2
Measures of socioeconomic inequality (Dissimilarity Indices) for the adoption of LCTs.

Specifications	SOLARPV (1)	SOLARHEAT (2)	HYBRIDEV (3)
	Panel A. Wave 4		
θ_I	0.277***	0.362***	0.382***
	(0.004)	(0.003)	(0.002)
	Panel B. Wave 10		
θ_I	0.203***	0.260***	0.298***
	(0.005)	(0.003)	(0.004)

Notes: Bootstrapped standard errors in parentheses (500 replications). Analysis is weighted using sample weights.
*** $p < 0.01$.

[6] Although income is potentially correlated with LCT adoption inequalities, it is important to emphasise that we focus on *predetermined* circumstances. Income is a later life outcome determined by one's effort and idiosyncratic characteristics.

[7] We create seven indicator variables for the following birth cohorts: those born before 1934; born between 1935 and 1944; born between 1945 and 1954; born between 1955 and 1964; born between 1965 and 1974; born between 1975 and 1984; and born after 1985.

[8] Age may be used as an alternative variable instead of birth cohorts. However, we believe that birth cohorts provide a more relevant interpretation as they better reflect the hypothesised variations in adoption patterns across generations.

[9] The occupational skill levels used to construct these variables are based on the Standard Occupational Classification 2010.

[10] Tables A3-A8 in the Appendix present the underlying reduced-form regression models (Equation 2).

been associated with a more equal distribution of these technologies across our set of socioeconomic factors. Specifically, the estimated dissimilarity index for solar panels used for electricity has declined from 0.277 in Wave 4 to 0.203 in Wave 10, a 27 % reduction in the level of socioeconomic inequalities. Similarly, we observe a 28 % (22 %) reduction in socioeconomic inequality in solar water heating adoption (low-carbon vehicles) over the same period (i.e., over a 6-year period from baseline Wave 4, collected in January 2012 – May 2014, to Wave 10). Overall, despite the observed reduction in magnitude, the observed socioeconomic inequalities in LCT are still non-negligible in magnitude at Wave 10.[11]

3.2. Decomposition of the observed socioeconomic inequality in LCTs

The results of the Shapley-Shorrocks decomposition in Table 3 allow us to explore the relative contribution of each of our circumstance variables to overall socioeconomic inequality. We note that the Shapley-Shorrocks decomposition allows us to estimate the contribution of each of our circumstances variables to the total *explained* socioeconomic inequality[12] and does not account for any potential unexplained variations in outcome variables that are not attributed to our set of socioeconomic circumstances. A graphical representation of these results is available in the Appendix (Fig. A1). Overall, along with the observed reduction in socioeconomic inequality in the adoption of LCTs over time (Table 2), we also observe variations in the contribution of the circumstance variables within the explained socioeconomic inequality.

With respect to the explained socioeconomic inequality in the adoption of solar panels for electricity (Column 1), birth cohort is the most notable contributor to socioeconomic inequality, but its relative contribution has decreased over time (47 % in Wave 4 vs 42 % in Wave 10); an individual's education remained the second most important contributor (20 % in Wave 10), while parental education and ethnicity became the third joint most important contributors at around 11 % in Wave 10.

Turning to solar water heating in Column 2, we observe variations in the most important contributors to socioeconomic inequality over time. Birth cohort (about 30 %), parental occupation (22 %), parental education (21 %) and an individual's education (19 %) are the most important contributors to socioeconomic inequality in the adoption of solar for heating water at the baseline (Wave 4); yet there is a shift in the top contributors in Wave 10, with parental occupation (38 %), parental education (21 %) and an individual's education (17 %) being the first, second and third contributing factors to socioeconomic inequality.

A shift in the order of the top contributing factors in socioeconomic inequality is also observed in the adoption of low-carbon vehicles (Column 3). Specifically, an individual's education (about 41 %), birth cohorts (19 %) and parental occupation (16 %) became the first, second and third in the order of contributing factors in Wave 10; the corresponding order of their relative contribution to socioeconomic inequality in low-carbon vehicles adoption in the baseline case (Wave 4) is parental occupation (at almost 39 %), followed by an individual's education (26 %) and parental education (22 %).

Across all LCTs we also observe a shift towards a larger contribution of gender and ethnicity in explaining the reduced socioeconomic inequalities over time, however, their contributions remain relatively low compared to all other circumstances. Overall, along with the observed reduction in socioeconomic inequality in LCT adoption over time, our decomposition results show that an individual's own education, parental occupation and education (and birth cohort for the case of solar panels for electricity) remained the most prominent contributors.

Table 3
Decomposition of socioeconomic inequality (Dissimilarity Indices) in adoption of LCT outcomes.

Specifications	SOLARPV (1)	SOLARHEAT (2)	HYBRIDEV (3)
		Panel A. Wave 4	
θ_I	**0.277**	**0.362**	**0.382**
		Contributions to inequality (%)	
Gender	4.98 %	6.08 %	3.18 %
Birth cohort	47.19 %	29.80 %	9.88 %
Ethnicity	5.67 %	3.03 %	0.02 %
Education	17.74 %	19.22 %	26.12 %
Parental occupation	17.72 %	21.69 %	38.60 %
Parental education	6.70 %	20.18 %	22.20 %
Total	**100 %**	**100 %**	**100 %**
		Panel B. Wave 10	
θ_I	**0.203**	**0.260**	**0.298**
		Contributions to inequality (%)	
Gender	8.39 %	7.22 %	5.69 %
Birth cohort	41.89 %	5.76 %	19.00 %
Ethnicity	10.99 %	9.75 %	3.83 %
Education	20.36 %	17.88 %	40.83 %
Parental occupation	7.19 %	38.01 %	16.41 %
Parental education	11.18 %	21.39 %	14.24 %
Total	**100 %**	**100 %**	**100 %**

3.3. Distributional patterns of adoption of LCTs over time and by socioeconomic inequality

Our analysis so far shows the presence of systematic socioeconomic inequality in LCTs, which has reduced in magnitude over the last decade along with increased LCT adoption levels. However, a closer examination of the longitudinal LCT adoption patterns, along with the socioeconomic inequalities observed among those who consistently adopt/do-not-adopt LCTs and those transitioning into or out of LCT adoption, could provide valuable insights into the factors driving the observed reduction in socioeconomic inequality in LCT adoption over time.

Table 4 describes the distribution of adoption of LCTs over time in our sample; it presents all the observed sequences of adoption of LCTs in Waves 4 and 10, resulting in ($2^2 = 4$) distinct sequences for each technology adoption outcome. Across all LCT outcomes, most respondents are characterised as persistent non-adopters ("No, No" sequences) within Wave 4 and Wave 10, with the corresponding proportions

Table 4
Distribution of adoption of LCTs across Waves 4 and 10 (balanced sample = 25,167).

	Low-carbon technology		Distribution	
Variables	Wave 4	Wave 10	Frequency	Percent
SOLARPV	No	No	23,635	93.91
	Yes	No	148	0.59
	No	Yes	926	3.68
	Yes	Yes	458	1.82
SOLARHEAT	No	No	24,587	97.70
	Yes	No	117	0.46
	No	Yes	267	1.06
	Yes	Yes	196	0.78
HYBRIDEV	No	No	24,513	97.40
	Yes	No	45	0.18
	No	Yes	562	2.23
	Yes	Yes	47	0.19

[11] Table A2 in the Appendix presents the corresponding inequality results (based on eq. 2 and 3 in our Methodology and Data section) from dissimilarity indexes applied to predictions from Logit, rather than Probit, regression models as in our base-case presented in Table 2. The socio-economic inequality in LCTs adoption results from our sensitivity analysis using Logit regression models (Table A2 in the Appendix) are practically identical to those presented in Table 2.

[12] As defined using the predicted counterfactual of our outcome variables in equation (3).

ranging between 93.9 % and 97.7 %; persistent adopters ("Yes, Yes" sequences) constitute between 0.2 % and 1.8 % of our sample across the LCT measures. Turning to sequences reflecting transitions over time, transitions towards adoption of LCT from non-adoption at the baseline ("No, Yes" sequences in Table 4) are the dominant sequences. For example, about 3.7 % of our sample reported no solar panels for electricity at the baseline (Wave 4) but have adopted this technology at Wave 10; the proportion transitioning to the adoption of solar for water heating and the ownership of low-carbon vehicles is about 1.1 % and 2.2 %, respectively.

Fig. 1 presents estimates of socioeconomic inequality measures when restricting our sample to certain longitudinal sequences of LCT adoption.[13] For all our LCT adoption outcomes, socioeconomic inequalities are systematically higher when considering the sample of persistent adopters and non-adopters ("NNYY") compared to the full sample for Waves 4 and 10 (presented in Table 2 and as "Main Sample (Table 2)" in Fig. 1 for comparison purposes). This shows that socioeconomic inequalities are much larger for those who do not make LCT adoption transitions over time. It should be noted that, as expected, the increased socioeconomic inequalities observed when restricting our sample to persistent adopters and non-adopters ("NNYY") are identical in both Waves 4 and 10, because there are no variations in the outcome variables and given that time-invariant set of circumstances are employed.

To provide insights on what drives the aforementioned larger socioeconomic inequalities for persistent adopters and non-adopters, we augment our sample of persistent adopters and non-adopters ("NNYY") to include (separately) those transiting to a) non-adoption ("NNYYYN") and b) adoption of LCTs ("NNYYNY").[14] Fig. 1 shows the impact of augmenting the sample of persistent non-adopters and adopters with respondents transitioning towards adopting an LCT between Waves 4 and 10 ("NNYYNY"). The socioeconomic inequality measures observed for the "NNYYNY" sub-sample follow similar patterns to those observed for our full sample, confirming higher socioeconomic inequalities in Wave 4 compared to Wave 10. Specifically, when comparing inequality results (across all LCT measures) between the "NNYY" and "NNYYNY" sub-samples, a substantial reduction in inequality is evident in the "NNYYNY" sub-sample for Wave 10 relative to the "NNYY" results. This suggests that the new adopters at Wave 10 tend to make LCT adoption less unequally distributed across our predetermined socioeconomic circumstances; this is also reflected in the observed broadly similar inequality patterns between "NNYYNY" and our "Main Sample (Table 2)" for both Waves 4 and 10 (Fig. 1).

On the other hand, Fig. 1 also shows a marked *increase* in LCT inequalities in Wave 10 when augmenting the sample of persistent non-adopters and adopters with those transitioning to non-adoption ("NNYYYN") across all LCTs compared to our "Main Sample" results. Hence, we may infer that the more disadvantaged individuals were unable to retain LCTs, as inequalities increase in Wave 10 when respondents who relinquished LCTs over time are included.

Overall, these results seem to indicate that the observed reduction in inequalities over time (between Waves 4 and 10) in the main sample (Table 2) is driven by those displaying transitory LCT adoption patterns between Waves 4 and 10, and more specifically those who recently adopted LCTs. The latter can be inferred by the similarity between the "NNYYNY" and the main sample results for both Waves 4 and 10 in Fig. 1 and given that the respondents who relinquished LCTs between the two waves are likely to be mostly socioeconomically disadvantaged.

Finally, the Shapley-Shorrocks decomposition is implemented to explore the underlying sources of socioeconomic inequality in those who never change their LCT adoption patterns (i.e., the persistent adopters and non-adopters) – this is of particular interest given that higher socioeconomic inequality is observed for this sub-sample of the population. The corresponding decomposition results are presented in Table 5.[15]

Table 5 shows that birth cohort, parental occupation, and parental education are the top three sources of the higher socioeconomic inequalities observed in the adoption of solar panels for the use of electricity (*SOLARPV*) in the sample of persistent adopters and non-adopters. In contrast, parental occupation, parental education, birth cohort and an individual's education are the key contributing factors to the observed inequalities in solar water heating (*SOLARHEAT*).

For low-carbon vehicles' ownership (Table 5, Column 3), parental occupation, an individual's education and parental education are the first, second and third contributing factors in order of magnitude. Compared to the corresponding decomposition results for Wave 10 in our full sample, we observe a notable shift towards a larger contribution of parental occupation and a reduced contribution of an individual's own education when excluding any individuals who changed their adoption pattern (Table 5, Column 3 vs Table 3, Column 3).

4. Discussion and conclusions

The adoption of LCTs by residential consumers is a cornerstone of the UK's target of net zero carbon emissions by 2050. However, the adoption of LCTs may not be equally distributed across socioeconomic groups in the UK population. Using a set of predetermined socioeconomic factors, we identified systematic and relatively large (in magnitude) socioeconomic inequalities in the adoption of LCTs. Our findings add to the existing literature by revealing that the socioeconomic inequality in LCT adoption is decreasing over time: for all LCTs considered (solar photovoltaics for electricity, solar water heating, and hybrid/electric vehicles) our measures of socioeconomic inequality decreased over the last decade while remaining highly statistically significant.

Socioeconomic inequality has fallen for solar water heating and solar panels for electricity over the last decade (about a 28 % reduction in their inequality levels). This could lead to important policy implications not least because heating forms the largest share of UK household energy bills. The percentage reduction in socioeconomic inequality in the adoption of hybrid/electric vehicles is lower (22 %) than for the other LCTs over the same time period. The UK government still subsidises some types of EVs at the point of sale, but these subsidies could be better targeted towards individuals (or communities) in disadvantaged socioeconomic circumstances. For example, the plug-in van grant, offering a discount on the price of new low-emission vehicles, and the government's subsidy towards the cost of homeplace charge-points for people living in flats are mainly independent of the socioeconomic status of the recipients (HM Government, 2021b). Our analysis, revealing socioeconomic inequality in EV ownership, suggests that they are still more likely to be adopted by the higher socioeconomic groups; thus, the implementation of unconditional subsidisation schemes may not sufficiently

[13] A table of the corresponding results is available in the Appendix (Table A9). As a sensitivity analysis, the corresponding inequality results based on dissimilarity indexes applied to predictions from Logit regression models are presented in Table A10 in the Appendix. These results are practically identical to our base-case results presented in Figure 1 and Table A9 in the Appendix.

[14] This analysis allows us to compare inequality results of the sub-sample of persistent adopters/non-adopters augmented with those transiting to LCTs non-adoption (NNYYYN) as well as the sub-sample of persistent adopters/non-adopters augmented with those transiting to LCT adoption (NNYYNY) with our main sample results. Thereby allowing for inferences about the role of LCT transistors (to adoption vs to non-adoption) when exploring the observed evolution of socioeconomic inequality patterns over time. Sample size prevents us from analysing socioeconomic inequality for the LCT transistors to adoption vs non-adoption itself (i.e., estimate socioeconomic inequality *separately* for the LCT transistors to adoption vs the LCT transistors to non-adoption).

[15] As noted earlier (and expected), socioeconomic inequalities are identical for both Waves 4 and 10 when restricting our sample to persistent adopters and non-adopters and, thus, the same holds for the corresponding decomposition results.

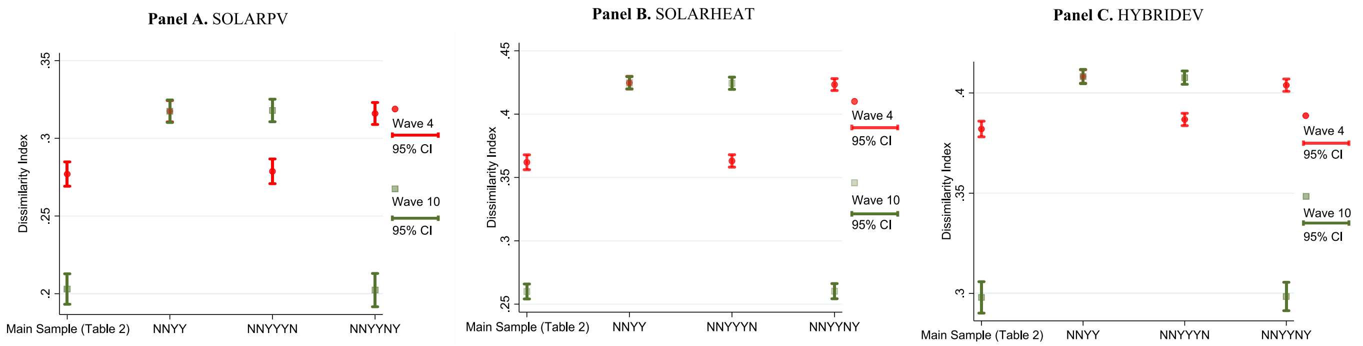

Fig. 1. Socioeconomic inequality of LCT adoption: analysis by subsets of longitudinal adoption patterns.
Note: This figure presents estimates of socioeconomic inequality measures when restricting our sample to specific longitudinal sequences of adoption of LCTs. For each Panel, corresponding to each of our LCT adoption outcomes, the results under the label "Main Sample (Table 2)" present our socioeconomic inequality results for our main sample separately for Wave 4 and Wave 10 (also available in Table 2). Then, we present socioeconomic inequality results when focusing only on those who are persistently adopters/non-adopters (NNYY) – as they are the same individuals and we employ time invariant predetermined circumstances, these results are by definition identical for both Wave 4 and Wave 10. Under the label "NNYYYN" we present inequality results augmenting the sample of persistent adopters/non-adopters (NNYY) to include those transiting to non-adoption; these results are presented separately for the Wave 4 and Wave 10 samples. Finally, under the label "NNYYNY" we present inequality results (separately for Wave 4 and 10) augmenting the sample of persistent adopters/non-adopters (NNYY) to include those transiting to LCTs adoption.

Table 5
Decomposition of socioeconomic inequality (Dissimilarity Indices) in measures of adoption of low-carbon technology: sub-sample constrained to persistent adopters/non-adopters (YES, YES; NO, NO).

Specifications	SOLARPV (1)	SOLARHEAT (2)	HYBRIDEV (3)
θ_I	**0.317**	**0.425**	**0.408**
		Contributions to inequality (%)	
Gender	5.44 %	5.94 %	2.49 %
Birth cohort	49.24 %	16.66 %	10.68 %
Ethnicity	6.74 %	9.04 %	0.52 %
Education	14.71 %	13.99 %	19.90 %
Parental occupation	16.12 %	31.57 %	48.16 %
Parental education	7.75 %	22.80 %	18.24 %
Total	**100 %**	**100 %**	**100 %**

increase take-up among disadvantaged socioeconomic groups. On the other hand, more targeted policy interventions for those of lower socioeconomic position, broader policies covering more LCTs and policies to increase awareness of the benefits of LCTs may be more effective in mitigating socioeconomic inequalities in the adoption of LCTs which, although reduced over time, are still more prevalent among those from a more disadvantaged socioeconomic background.

By exploiting the availability of longitudinal data, we established further important empirical findings: a) socioeconomic inequality is highest for those persistently adopting (innovators) and those persistently not adopting; b) the innovators that relinquished their LCTs over time are more likely to experience disadvantaged socioeconomic circumstances; and c) more recent adopters (early-adopters) contributed to the reduced socioeconomic inequality in LCT adoption over the last decade. This last observation would suggest that the low-carbon transition is being increasingly made by more disadvantaged individuals.

The decomposition analysis of the observed socioeconomic inequality in LCT adoption shows that while birth cohort, own education, parental education and parental occupation remain the four main contributors, gender and ethnicity represent a smaller but growing share of socioeconomic inequality. These results reveal the total contribution of predetermined factors in shaping inequalities in LCT adoption — via their direct and indirect effects on people's later life efforts and socioeconomic circumstances that may affect LCT adoption.

From a normative point of view, inequalities in LCT adoption which are driven by socioeconomic background during childhood are considered unfair sources of inequality leading to calls for regulatory interventions. The limited related literature aligns broadly with our findings, suggesting, for instance, that early-life education can serve as a pathway to improving technology adoption (Kämpfen and Maurer, 2018). Hence a multifaceted approach to policy design which accounts for intergenerational effects is necessary to support the low-carbon transition (Schot and Kanger, 2018).

Our findings also add to the growing debate on the potential economic (in)efficiency of individual uptake of LCTs, and on the problems created for vulnerable consumers by these inefficiencies compared to the effects of an unequal distribution of LCTs. For example, in the context of solar panel adoption, rather than advocate for solar panels for individual households, Borenstein (2022) argues for a shift towards community or utility-scale installations; these community/utility-scale installations could alleviate the burden of costly adoption and help to reduce energy bills. Other scholars suggest that targeted cost-based interventions could be introduced to level the playing field (Best et al., 2021; Ravigné et al., 2022). It is crucial therefore to promote LCT adoption by the most vulnerable, either at the household or community level, not least because socioeconomic inequality in LCTs may hinder successful pathways to carbon abatement.

Our study is not free of limitations and should be viewed as an attempt to measure socioeconomic inequality in LCT adoption and its underlying sources, rather than providing a causal analysis of the link between adverse circumstances and LCT adoption. Endogeneity concerns may arise, for example, due to the omission of relevant unobservable circumstances, although we employ a set of carefully selected predetermined variables. Even in the presence of such unobserved circumstances, our inequality measures can be interpreted as lower-bound estimates of the overall inequality due to all (observed and unobserved) circumstances (Davillas and Jones, 2020; Ferreira and Gignoux, 2011). Exploring the role of socioeconomic inequalities in the adoption of energy efficiency measures is beyond the scope of the present paper, as the relevant data is currently unavailable in UKHLS. Nonetheless, this is a worthy avenue for future research given the need for improved energy efficiency in order to achieve net zero targets.

Finally, it is important to emphasise that the presence of socioeconomic inequalities in LCT adoption may exacerbate broader socioeconomic inequalities by limiting the ability of the most disadvantaged to invest in technology which could lower their energy costs. Our results lead us to support policies targeting specific disadvantaged socioeconomic groups; this is not only crucial to mitigate the observed inequalities in LCT adoption but also relevant in promoting energy efficiency and resilience to high energy prices as we transition towards a low-carbon future.

CRediT authorship contribution statement

Andrew Burlinson: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Apostolos Davillas:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Monica Giulietti:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Acknowledgments

We are grateful to two anonymous reviewers for their comments on a previous version of the manuscript which have helped us to produce a much improved article.

The research was undertaken as part of the UK Energy Research Centre research programme. This work was funded by the UKERC Flexible Fund under grant number EP/SO29575/1.

The data used in this research work has been obtained from the Understanding Society survey. Understanding Society is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. The research data are distributed by the UK Data Service. The funders, data creators and UK Data Service have no responsibility for the contents of this paper.

Appendix A. Appendix

Table A1
Variables' definitions and mean values (balanced sample).

		Definition	Mean
Gender			
FEMALE (reference)		1 if female; 0 otherwise	0.588
MALE		1 if male; 0 otherwise	0.412
Birth cohort			
BEFORE-1934 (reference)		1 if born before 1934; 0 otherwise	0.045
1935–1944		1 if born between 1935 and 1944; 0 otherwise	0.149
1945–1954		1 if born between 1945 and 1954; 0 otherwise	0.252
1955–1964		1 if born between 1955 and 1964; 0 otherwise	0.236
1965–1974		1 if born between 1965 and 1974; 0 otherwise	0.197
1975–1984		1 if born between 1975 and 1984; 0 otherwise	0.094
AFTER_1985		1 if born after 1985; 0 otherwise	0.028
Ethnicity			
NON-WHITE (reference)		1 if non-white; 0 otherwise	0.085
WHITE		1 if white; 0 otherwise	0.915
Education			
NOQUALS (reference)		1 if no qualifications; 0 otherwise	0.309
BASICQUALS		1 if basic qualifications; 0 otherwise	0.322
OLEVELS		1 if O-level qualification; 0 otherwise	0.180
ALEVELS		1 if A-level qualification; 0 otherwise	0.096
DEGREE		1 if degree qualification; 0 otherwise	0.092
Parental occupation			
MOTHER-OCCUPATION-	NOTWORKING	1 if mother was not working (when respondent was 14), 0 otherwise	0.417
	SLEVEL1	1 if mother's job was skilled level 1 (when respondent was 14), 0 otherwise	0.065
	SLEVEL2	1 if mother's job was skilled level 2 (when respondent was 14), 0 otherwise	0.055
	SLEVEL3	1 if mother's job was skilled level 3 (when respondent was 14), 0 otherwise	0.183
	SLEVEL4(reference)	1 if mother's job was skilled level 4 (when respondent was 14), 0 otherwise	0.097
	MISSING	1 if mother's job market status is missing, 0 otherwise	0.183
FATHER-OCCUPATION	NOTWORKING	1 if father was not working (when respondent was 14), 0 otherwise	0.044
	SLEVEL1	1 if father's job was skilled level 1 (when respondent was 14), 0 otherwise	0.125
	SLEVEL2	1 if father's job was skilled level 2 (when respondent was 14), 0 otherwise	0.283
	SLEVEL3	1 if father's job was skilled level 3 (when respondent was 14), 0 otherwise	0.162
	SLEVEL4(reference)	1 if father's job was skilled level 4 (when respondent was 14), 0 otherwise	0.057
	MISSING	1 if father's job market status is missing, 0 otherwise	0.329
Parental education			
HIGHEST EDUCATION	NONE (reference)	1 if parents' highest qualification is left school with no/some qualification, 0 otherwise	0.528
	POSTSCHOOL	1 if parents' highest qualification is post-school/certificate, 0 otherwise	0.254
	DEGREE	1 if parents' highest qualification is degree level, 0 otherwise	0.103
	EDUMISSING	1 if parents' highest is unknown or missing, 0 otherwise	0.115

Notes: Mean values are weighted using sample weights. Balanced sample of UKHLS Waves 4 and 10.

Table A2
Measures of socioeconomic inequality (Dissimilarity Indices) for the adoption of LCTs: Logit regression for prediction.

Specifications	SOLARPV (1)	SOLARHEAT (2)	HYBRIDEV (3)
	Panel A. Wave 4		
θ_I	0.278***	0.362***	0.383***
	(0.004)	(0.003)	(0.002)
	Panel B. Wave 10		
θ_I	0.203***	0.260***	0.291***
	(0.005)	(0.003)	(0.004)

Notes: Bootstrapped standard errors in parentheses (500 replications). Analysis is weighted using sample weights.
*** $p < 0.01$.

Table A3
Reduced-form models (Probit and Logit): SOLARPV (Wave 4).

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
MALE	0.048	0.035	0.110	0.083
BIRTH COHORT[††]				
1935–1944	0.000	0.100	0.004	0.233
1945–1954	0.020	0.096	0.035	0.223
1955–1964	−0.142	0.098	−0.339	0.231
1965–1974	−0.342***	0.101	−0.820***	0.240
1975–1984	−0.607***	0.114	−1.521***	0.280
AFTER_1985	−0.327***	0.109	−0.779***	0.258
WHITE	0.061	0.061	0.146	0.150
EDUCATION[††]				
BASICQUALS	0.005	0.087	0.013	0.216
OLEVELS	0.144*	0.075	0.352*	0.185
ALEVELS	0.252***	0.070	0.602***	0.169
DEGREE	0.291***	0.074	0.706***	0.179
MOTHER-OCCUPATION				
NOTWORKING	0.113	0.080	0.271	0.193
SLEVEL1	0.079	0.098	0.173	0.237
SLEVEL2	0.106	0.085	0.250	0.204
SLEVEL3	0.142	0.102	0.331	0.244
MISSING	0.130	0.093	0.308	0.225
FATHER-OCCUPATION[††]				
NOTWORKING	−0.013	0.093	−0.021	0.218
SLEVEL1	−0.015	0.089	−0.033	0.208
SLEVEL2	−0.096	0.067	−0.213	0.158
SLEVEL3	−0.150***	0.056	−0.339***	0.130
MISSING	−0.171***	0.066	−0.393**	0.154
PARENTAL-EDUCATION[††]				
POSTSCHOOL	0.103**	0.046	0.251**	0.109
DEGREE	0.176***	0.066	0.417***	0.157
EDUMISSING	0.055	0.052	0.133	0.126
Constant	−2.111***	0.146	−4.050***	0.350

Likelihood ratio (LR) tests for the covariates included in the Probit and Logit models: p-value = 0.000.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.
Note: Robust standard errors are presented in the table.
[††] For each of these categorical variables, the relevant coefficients are jointly statistically significant at least at the 5 % level.

Table A4
Reduced-form models (Probit and Logit): SOLARPV (Wave 10).

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
MALE	0.071***	0.026	0.150***	0.054
BIRTH COHORT[††]				
1935–1944	0.201**	0.083	0.449**	0.190
1945–1954	0.347***	0.080	0.751***	0.183
1955–1964	0.368***	0.081	0.789***	0.185
1965–1974	0.213**	0.084	0.473**	0.190
1975–1984	0.051	0.092	0.114	0.209
AFTER_1985	−0.011	0.123	−0.012	0.278
WHITE	0.255***	0.056	0.548***	0.124
EDUCATION[††]				
BASICQUALS	0.201***	0.069	0.443***	0.153
OLEVELS	0.288***	0.062	0.635***	0.139
ALEVELS	0.328***	0.060	0.704***	0.134
DEGREE	0.353***	0.062	0.757***	0.138
MOTHER-OCCUPATION				
NOTWORKING	0.046	0.056	0.097	0.116
SLEVEL1	0.075	0.067	0.159	0.138
SLEVEL2	0.036	0.059	0.079	0.122
SLEVEL3	0.096	0.073	0.206	0.151
MISSING	0.039	0.066	0.084	0.138
FATHER-OCCUPATION				
NOTWORKING	−0.002	0.074	−0.006	0.155
SLEVEL1	0.092	0.066	0.163	0.134
SLEVEL2	0.005	0.050	0.010	0.102
SLEVEL3	−0.028	0.044	−0.061	0.091
MISSING	−0.028	0.049	−0.060	0.100
PARENTAL-EDUCATION[††]				
POSTSCHOOL	0.084***	0.032	0.176***	0.065
DEGREE	0.154***	0.047	0.322***	0.096
EDUMISSING	0.041	0.044	0.068	0.091
Constant	−2.416***	0.122	−4.615***	0.271

Likelihood ratio (LR) tests for the covariates included in the Probit and Logit models: p-value = 0.000.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.
Note: Robust standard errors are presented in the table.
[††] For each of these categorical variables, the relevant coefficients are jointly statistically significant at least at the 5 % level.

Table A5
Reduced-form models (Probit and Logit): SOLARHEAT (Wave 4).

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
MALE	0.046	0.045	0.115	0.114
BIRTH COHORT[††]				
1935–1944	−0.015	0.106	−0.031	0.260
1945–1954	−0.216**	0.104	−0.547**	0.259
1955–1964	−0.258***	0.107	−0.665***	0.266
1965–1974	−0.399***	0.113	−1.009***	0.281
1975–1984	−0.811***	0.152	−2.108***	0.410
AFTER_1985	−0.748***	0.219	−1.971***	0.613
WHITE	0.080	0.096	0.193	0.251
EDUCATION[††]				
BASICQUALS	0.178	0.122	0.458	0.334
OLEVELS	0.318***	0.110	0.859***	0.300
ALEVELS	0.332***	0.105	0.890***	0.287
DEGREE	0.478***	0.107	1.255***	0.292
MOTHER-OCCUPATION				
NOTWORKING	−0.005	0.090	−0.002	0.219
SLEVEL1	−0.120	0.119	−0.321	0.305
SLEVEL2	−0.045	0.098	−0.082	0.242
SLEVEL3	−0.070	0.127	−0.183	0.323
MISSING	0.045	0.110	0.130	0.276
FATHER-OCCUPATION[††]				
NOTWORKING	−0.124	0.126	−0.269	0.318
SLEVEL1	−0.018	0.108	−0.014	0.268
SLEVEL2	−0.264***	0.085	−0.642***	0.216
SLEVEL3	−0.159**	0.069	−0.370**	0.170
MISSING	−0.257***	0.079	−0.631***	0.197
PARENTAL-EDUCATION[††]				
POSTSCHOOL	0.158***	0.055	0.425***	0.141
DEGREE	0.236***	0.078	0.593***	0.193

(continued on next page)

Table A5 (*continued*)

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
EDUMISSING	0.215***	0.073	0.550***	0.186
Constant	−2.305***	0.185	−4.621***	0.480

Likelihood ratio (LR) tests for the covariates included in the Probit and Logit models: p-value = 0.000.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.
Note: Robust standard errors are presented in the table.
[††] For each of these categorical variables, the relevant coefficients are jointly statistically significant at least at the 5 % level.

Table A6
Reduced-form models (Probit and Logit): SOLARHEAT (Wave 10).

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
MALE	0.065	0.053	0.150	0.129
BIRTH COHORT				
1935–1944	0.152	0.144	0.382	0.363
1945–1954	0.061	0.143	0.151	0.364
1955–1964	0.062	0.149	0.141	0.376
1965–1974	0.079	0.150	0.171	0.378
1975–1984	−0.002	0.167	−0.030	0.422
AFTER_1985	0.067	0.225	0.145	0.560
WHITE	0.300**	0.116	0.744**	0.305
EDUCATION[††]				
BASICQUALS	0.142	0.142	0.362	0.374
OLEVELS	0.243*	0.129	0.626*	0.337
ALEVELS	0.268**	0.123	0.685**	0.326
DEGREE	0.315**	0.127	0.800**	0.335
MOTHER-OCCUPATION				
NOTWORKING	0.197	0.127	0.446	0.384
SLEVEL1	0.045	0.145	0.081	0.358
SLEVEL2	0.056	0.127	0.127	0.314
SLEVEL3	−0.004	0.161	−0.008	0.398
MISSING	0.234*	0.136	0.551*	0.335
FATHER-OCCUPATION[††]				
NOTWORKING	−0.353**	0.165	−0.861**	0.430
SLEVEL1	−0.098	0.144	−0.256	0.352
SLEVEL2	−0.209**	0.105	−0.502**	0.249
SLEVEL3	−0.010	0.087	−0.024	0.206
MISSING	−0.266***	0.095	−0.643***	0.227
PARENTAL-EDUCATION[††]				
POSTSCHOOL	0.109*	0.062	0.269*	0.152
DEGREE	0.188**	0.094	0.441*	0.226
EDUMISSING	0.093	0.085	0.227	0.210
Constant	−2.733***	0.230	−5.572***	0.588

Likelihood ratio (LR) tests for the covariates included in the Probit and Logit models: p-value = 0.000.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.
Note: Robust standard errors are presented in the table.
[††] For each of these categorical variables, the relevant coefficients are jointly statistically significant at least at the 5 % level.

Table A7
Reduced-form models (Probit and Logit): HYBRIDEV (Wave 4).

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
MALE	−0.011	0.072	−0.045	0.214
BIRTH COHORT				
1935–1944	0.037	0.249	0.196	0.762
1945–1954	0.009	0.237	0.084	0.720
1955–1964	0.044	0.233	0.202	0.704
1965–1974	−0.016	0.236	0.015	0.709
1975–1984	−0.268	0.244	−0.694	0.744
AFTER_1985	−0.117	0.247	−0.249	0.747
WHITE	−0.048	0.102	−0.115	0.301
EDUCATION[††]				
BASICQUALS	0.410*	0.235	1.353*	0.796
OLEVELS	0.208	0.231	0.713	0.795
ALEVELS	0.511**	0.210	1.667**	0.726
DEGREE	0.668***	0.215	2.093***	0.737
MOTHER-OCCUPATION				

(*continued on next page*)

Table A7 (*continued*)

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
NOTWORKING	0.143	0.152	0.431	0.448
SLEVEL1	0.278	0.180	0.793	0.531
SLEVEL2	0.189	0.157	0.558	0.462
SLEVEL3	−0.021	0.210	−0.051	0.636
MISSING	0.029	0.181	0.067	0.544
FATHER-OCCUPATION				
NOTWORKING	0.036	0.182	0.133	0.531
SLEVEL1	−0.188	0.210	−0.515	0.650
SLEVEL2	−0.034	0.135	−0.088	0.394
SLEVEL3	0.066	0.117	0.204	0.336
MISSING	−0.142	0.136	−0.396	0.407
PARENTAL-EDUCATION				
POSTSCHOOL	0.119	0.091	0.371	0.271
DEGREE	0.223*	0.121	0.642*	0.348
EDUMISSING	0.128	0.105	0.362	0.314
Constant	−3.273***	0.397	−7.608***	1.276

Likelihood ratio (LR) tests for the covariates included in the Probit and Logit models: p-value = 0.000.
Note: Robust standard errors are presented in the table.
*** p < 0.01; ** p < 0.05; * p < 0.10.
†† For each of these categorical variables, the relevant coefficients are jointly statistically significant at least at the 5 % level.

Table A8
Reduced-form models (Probit and Logit): HYBRIDEV (Wave 10).

	Probit		Logit	
	Coef.	Std. Err.	Coef.	Std. Err.
MALE	0.093**	0.040	0.217**	0.093
BIRTH COHORT††				
1935–1944	0.095	0.150	0.272	0.393
1945–1954	0.245**	0.143	0.641*	0.373
1955–1964	0.284**	0.144	0.729**	0.364
1965–1974	0.284**	0.145	0.729**	0.365
1975–1984	0.247*	0.149	0.662*	0.385
AFTER_1985	0.062	0.162	0.221	0.416
WHITE	−0.196***	0.055	−0.431***	0.123
EDUCATION††				
BASICQUALS	0.099	0.117	0.235	0.299
OLEVELS	0.109	0.104	0.268	0.266
ALEVELS	0.213**	0.097	0.520**	0.248
DEGREE	0.426***	0.097	1.011***	0.246
MOTHER-OCCUPATION				
NOTWORKING	0.052	0.080	0.111	0.179
SLEVEL1	0.067	0.101	0.125	0.232
SLEVEL2	0.054	0.085	0.108	0.191
SLEVEL3	−0.142	0.117	−0.348	0.274
MISSING	0.013	0.097	0.017	0.223
FATHER-OCCUPATION				
NOTWORKING	−0.027	0.101	−0.045	0.231
SLEVEL1	−0.076	0.106	−0.169	0.248
SLEVEL2	−0.106	0.076	−0.253	0.176
SLEVEL3	−0.005	0.065	−0.002	0.147
MISSING	−0.165*	0.073	−0.381**	0.169
PARENTAL-EDUCATION†				
POSTSCHOOL	−0.004	0.052	−0.006	0.123
DEGREE	0.157**	0.067	0.323**	0.151
EDUMISSING	−0.003	0.059	−0.012	0.139
Constant	−2.274***	0.186	−4.504***	0.470

Likelihood ratio (LR) tests for the covariates included in the Probit and Logit models: p-value = 0.000.
*** p < 0.01; ** p < 0.05; * p < 0.10.
Note: Robust standard errors are presented in the table.
†† For each of these categorical variables, the relevant coefficients are jointly statistically significant at least at the 5 % level.
† The relevant coefficient for the parental education categorical variable are jointly statistically significant at the 10 % level.

Table A9
Socioeconomic inequality (Dissimilarity Indices) in LCT adoption: constrained to different subsets of longitudinal adoption patterns.

Specifications	SOLARPV (1)	SOLARHEAT (2)	HYBRIDEV (3)
	Panel A. Wave 4		
θ_I: ALL	0.277***	0.362***	0.382***
	(0.004)	(0.003)	(0.002)
θ_I: NNYY	0.317***	0.425***	0.408***
	(0.004)	(0.003)	(0.002)
θ_I: NNYYYN	0.279***	0.363***	0.387***
	(0.004)	(0.002)	(0.002)
θ_I: NNYYNY	0.316***	0.423***	0.404***
	(0.004)	(0.002)	(0.002)
	Panel B. Wave 10		
θ_I ALL	0.203***	0.260***	0.298***
	(0.005)	(0.003)	(0.004)
θ_I: NNYY	0.317***	0.425***	0.408***
	(0.004)	(0.002)	(0.002)
θ_I: NNYYYN	0.318***	0.424***	0.408***
	(0.004)	(0.002)	(0.002)
θ_I: NNYYNY	0.202***	0.26***	0.298***
	(0.005)	(0.003)	(0.004)

Notes: Bootstrapped standard errors in parentheses (500 replications). Analysis is weighted using sample weights.
*** $p < 0.01$.

Table A10
Socioeconomic inequality (Dissimilarity Indices) in LCT adoption using Logit regression for prediction: constrained to different subsets of longitudinal adoption patterns.

Specifications	SOLARPV (1)	SOLARHEAT (2)	HYBRIDEV (3)
	Panel A. Wave 4		
θ_I: ALL	0.278***	0.362***	0.383***
	(0.004)	(0.003)	(0.002)
θ_I: NNYY	0.318***	0.424***	0.406***
	(0.004)	(0.002)	(0.002)
θ_I: NNYYYN	0.280***	0.363***	0.388***
	(0.004)	(0.003)	(0.002)
θ_I: NNYYNY	0.316***	0.422***	0.402***
	(0.004)	(0.003)	(0.002)
	Panel B. Wave 10		
θ_I ALL	0.203***	0.260***	0.291***
	(0.005)	(0.003)	(0.004)
θ_I: NNYY	0.319***	0.424***	0.405***
	(0.004)	(0.002)	(0.002)
θ_I: NNYYYN	0.318***	0.424***	0.408***
	(0.004)	(0.002)	(0.002)
θ_I: NNYYNY	0.203***	0.260***	0.292***
	(0.005)	(0.003)	(0.004)

Notes: Bootstrapped standard errors in parentheses (500 replications). Analysis is weighted using sample weights.
*** p < 0.01.

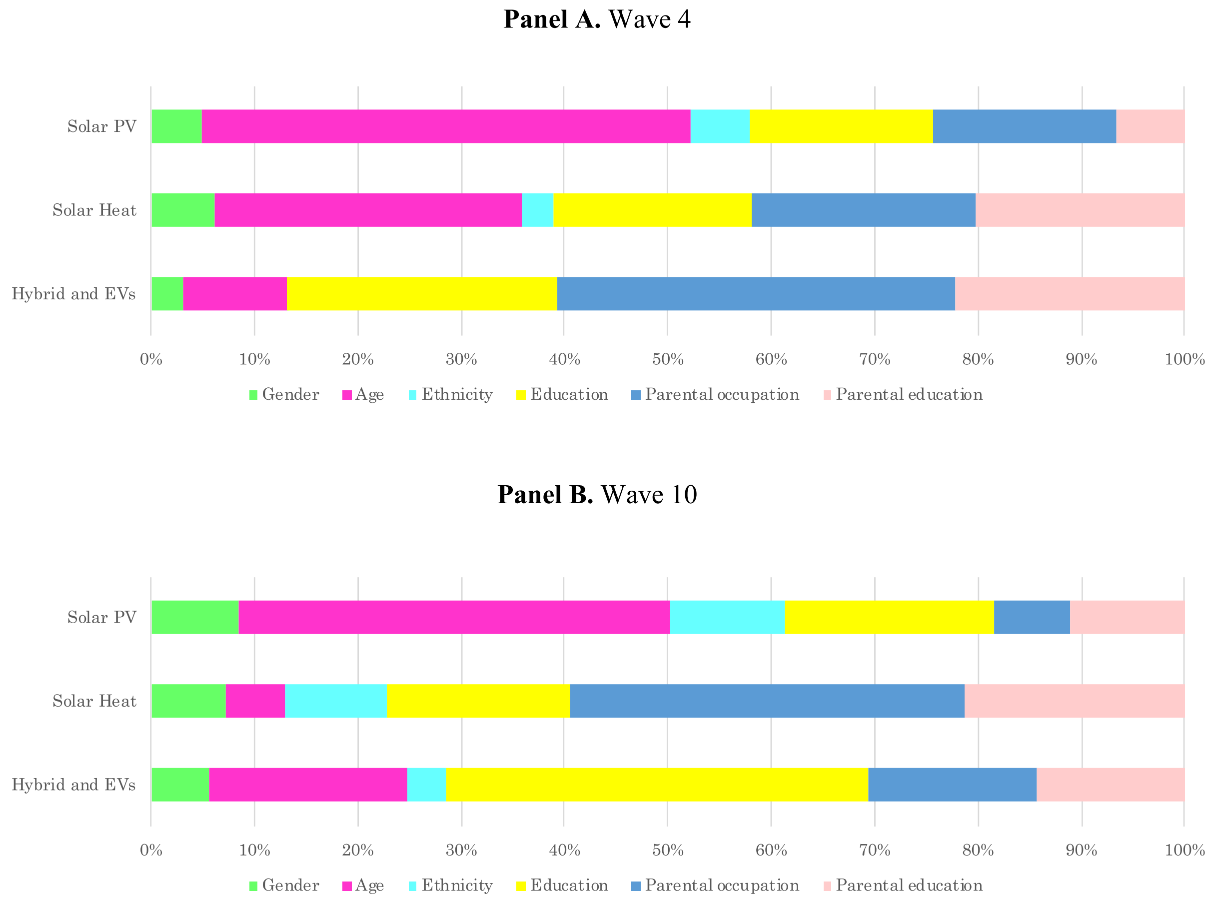

Fig. A1. Decomposition of socioeconomic inequality in LCT adoption outcomes.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108244.

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