Energy Economics 127 (2023) 107042

Contents lists available at ScienceDirect

Energy Economics

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

Regional persistence of the energy efficiency gap: Evidence from England and Wales

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ARTICLE INFO

JEL classification:
D12
Q40

Keywords:
Energy efficiency gap
Climate change
Retrofit, dynamic panel data models
Partial adjustment model

ABSTRACT

The pursuit of reducing imported energy dependence via energy efficiency measures has become crucial to achieving sustainability goals, reducing greenhouse gas emissions, and minimising reliance on imported energy. Despite the significant heterogeneity of energy dependence across regions, heavy reliance on energy imports can expose countries to energy security risks that impact wholesale market energy prices and global energy security, especially in periods of geopolitical conflict. Recent geopolitical conflicts and pent-up demand from post-pandemic recovery have caused global energy prices to rise, leading to high inflation and a severe cost-of-living crisis worldwide. The existence of persistent patterns of energy efficiency gap can quickly exacerbate the associated environmental and economic losses caused by energy price shocks. This paper aims to provide robust empirical evidence of the existence of patterns of persistence of the energy efficiency gap and analyses cross-sectional heterogeneity in such persistence. In a large sample of 18,361,088 domestic dwellings across England and Wales, this study incorporates observable cross-sectional heterogeneous factors, such as socioeconomic conditions, regional characteristics, and structural constraints, to understand the potential barriers preventing residents from adjusting their energy efficiency ratings and their energy efficiency gaps. Notably, the study finds that the energy efficiency gap exhibits an average high degree of persistence of almost 50%, a finding that is statistically and economically significant across all of the LSOAs in England and Wales. The study also finds significant evidence of cross-sectional heterogeneity. This analysis is unique, both in terms of methodology and the subject of investigation, as it is the first empirical analysis that investigates regional patterns of persistence of the energy efficiency gap across England and Wales with such a large degree of granularity. The findings of this study contribute to the scarce academic literature in the field and provide valuable information for designing effective policies that can help achieve energy security and climate change goals while tackling growing socioeconomic inequalities.

1. Introduction

Energy efficiency constitutes a crucial factor in achieving long-term sustainability goals, mitigating greenhouse gas emissions, and reducing reliance on energy imports. In 2020, Russia accounted for nearly 29% of crude oil and 43% of natural gas imports into the EU. While dependence on Russian energy varies significantly across regions, with countries in Central and Eastern Europe, Germany, and Italy displaying the greatest reliance, such dependence holds the potential to rapidly escalate energy security risks and influence wholesale market energy prices, thereby impacting global energy security. As a consequence, governments worldwide have implemented various economic policy responses, including the deferment of utility bills known as the Energy Price Guarantee (EPG), to safeguard their economies from the negative effects caused by pent-up demand resulting from the post-pandemic recovery and, more recently, from Russia's invasion of Ukraine.

Although both events have contributed to the surge in energy prices, Russia's invasion of Ukraine has had the most significant implications for global energy markets. Between February 23rd, the eve of Russia's invasion of Ukraine, and July 2022, global energy prices steadily rose, reaching record-high levels by the end of July 2022. As a result, European gas and electricity wholesale prices increased by 115% and 237%, respectively. It is important to note that government interventions have extended beyond economic policy responses; substantial efforts have been made to diversify energy sources in an attempt to reduce dependence on Russian energy imports. These diversification initiatives, coupled with the development of alternative energy sources such as

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[1] The author is thankful to two anonymous referees and one of the handling editors for constructive comments and suggestions which has substantially improved the paper from its earlier version.

https://doi.org/10.1016/j.eneco.2023.107042
Received 29 April 2023; Received in revised form 3 September 2023; Accepted 10 September 2023
Available online 29 September 2023

renewables, have to some extent mitigated the negative consequences of high energy prices.

It is evident that countries' reliance on imported energy remains one of the greatest risks for governments striving to achieve their urgent priorities, including ensuring energy security, addressing climate change, and mitigating increasing levels of socioeconomic disparities. For instance, in the case of the UK, its reliance on imported energy has led to unprecedented increases in energy prices, to the extent that under the current EPG, the average annual gas and electricity bill for a customer paying by direct debit with 'typical' consumption levels is £2,500 from October 2022 to June 2023. This represents a 27% increase compared to the summer 2022 price cap and a 96% increase compared to the winter 2021/22 price cap. Gas prices have increased even more significantly during the same period, increasing by 141% since winter 2021/22, while electricity prices have seen a 65% increase (Bolton and Stewart, 2023).

From the above, it is clear that the unresolved geopolitical situation in Ukraine will continue to shape energy markets and influence government efforts to mitigate its consequences unless long-term energy security and net zero initiatives are promptly deployed. This is because energy security and net zero initiatives are two sides of the same coin, capable of driving the global transition to clean technologies, bringing down carbon emissions, safeguarding the environment, enhancing energy security, and realising the green growth economic opportunities offered by such a transition. In this context, "Powering Up Britain", the government's blueprint for the future of energy lays the foundations for a clean energy transition in line with net zero goals. This long-term energy policy framework builds upon the Prime Minister's Ten-point plan for a green industrial revolution[2], incorporating significant UK climate and energy policies, including the Energy White Paper[3], Net Zero Strategy[4], and the British Energy Security Strategy.[5] Through these measures, the government has made abundantly clear that the long-term solution to address the UK's underlying vulnerability to international fossil fuel prices is to establish a clean energy transition in line with net zero goals, thereby reducing dependence on imported oil and gas while fulfilling net zero commitments. Following this rationale, the UK will strategically ensure all four of its pressing priorities: energy security, consumer security, economic security, and climate security, becoming a thriving net zero economy by 2050[6].

However, while a clean energy transition in line with net zero strategies offers protection against volatile international energy markets and substantial opportunities for green economic growth, the current approach falls short of ensuring equitable, inclusive, and enduring economic development. This discrepancy contradicts three of the previously mentioned priorities, namely climate security, economic security, and consumer security. Presently, the climate-energy policy framework prioritises diversification, decarbonisation, and domestication of energy production in the UK[7], yet it lacks clarity regarding long-term strategies to reduce inefficient energy usage. This issue is of utmost concern due to the paramount role that energy efficiency improvement plays in achieving all levels of security mentioned above, for at least two reasons. Firstly, while the surge in energy prices and the ensuing economic consequences[8] are sadly expected to disproportionately affect households in the short run, with lower-income households bearing a heavier burden compared to wealthier counterparts[9]; the situation should equalise in the long run when energy prices are projected to be lower. However, the existence of persistent pockets of households' energy efficiency gaps (EEG), denoting the difference between the level of energy efficiency that can be achieved using existing and cost-effective technologies and the actual level of energy efficiency observed in dwellings, has the potential to permanently exacerbate the financial vulnerability of lower-income households. In other words, households with larger EEGs will consistently face higher energy bills than is expected given their financial constraints, rendering them more vulnerable than similar households with smaller EEGs.

Secondly, considering that emissions from households – accounted for through consumer expenditure (residence basis) – are the largest contributor to total UK emissions (ONS, 2023b)[10], persistent EEGs across regions pose a threat to policies aimed at mitigating the devastating effects of climate change while addressing growing disparities among people at different ends of the income distribution. This is due to the fact that homes with larger EEGs have higher energy demands and consequently are major contributors to greenhouse gas emissions. On the matter, the UK government asserts that between 1990 and 2021, the country reduced its emissions by 48%, outpacing any other G7 nation in decarbonisation, DESNZ (2023b). However, empirical studies demonstrate that most of this reduction stemmed from shifting away from coal production rather than enhancing energy efficiency (e.g., CarbonBrief, 2023). Notably, DESNZ (2023d) highlights that despite overall improvements in UK energy efficiency in 2022, there has not been an increase in the share of households living in properties rated band C or higher for fuel poverty energy efficiency over the past decades. The Climate Change Committee (CCC, 2022b)

2 DESNZ (2020b)

3 DESNZ (2020a)

4 BEIS (2021b)

5 BEIS (2022a)

6 In 2019, following the Climate Change Committee (CCC, 2019)'s recommendation, the UK became the first major economy to pass laws to bring all greenhouse gas emissions to net zero by 2050, compared with the previous target of at least 80% reduction from 1990 levels. In April 2021, the UK enshrined an even more ambitious target to reduce emissions by 78% by 2035 on 1990 levels. In October 2021 the government published 'Net Zero Strategy: Build back greener', which set out policies and proposals for decarbonising all sectors of the UK economy and meeting the net zero target by 2050, BEIS (2021b). CCC's recommendations are aligned with the goals outlined in the Paris Agreement (UNFCCC, 2015) and more recent Intergovernmental Panel on Climate Change (IPCC, 2023) as well as with the United Nations Environment Program (UNEP, 2022), which call for the recognition of the significant benefits of reducing the risks and impacts of climate change, keeping the global average temperature rise well below 2 °C above pre-industrial levels and actively striving to limit it to 1.5 °C above pre-industrial levels (Skidmore, 2019).

7 This will be achieved leveraging Britain's strategic geolocation, investing in renewables such as wind and solar, adopting technologies like Carbon Capture, Usage, and Storage, Floating Offshore Wind Manufacturing, hydrogen, and nuclear plans, with the aim of achieving the lowest wholesale electricity prices in Europe by 2035 (DESNZ, 2023c).

8 Recent statistical data from the UK's Office for National Statistics (ONS, 2023a) reveals that the annual Consumer Prices Index including owner-occupiers' housing costs (CPIH) rose by 8.9% in the 12 months to March 2023, down from 9.2% in February 2022 and from a peak of 9.6% in October 2022, with the largest upward contributions coming from housing and household services, particularly gas (128.9%) and electricity (65.7%).

9 According to the Financial Conduct Authority's findings, the number of adults who failed to make payments on their domestic bills or meet their credit obligations increased by 1.4 million. The figure rose from 4.2 million in May 2022 to 5.6 million in January 2023 (FCA, 2023). This situation poses a significant challenge for households with low incomes, as they are compelled to make difficult choices regarding how to allocate their limited financial resources. For example, they must determine the portion of their disposable income that can be devoted to weekly groceries, leaving them with less to cover essential needs like electricity, heating, and cooling (Huaccha, 2022; Meadway and Huaccha, 2023).

10 Data from the ONS (2023), UK Environmental Accounts: Measuring the contribution of the environment to the economy, impact of economic activity on the environment, and response to environmental issues, show that in 2021, emissions related to consumer expenditure – primarily driven by heating homes and travelling – rose 7% to 135 million tonnes of carbon dioxide equivalent (Mt Co2e), accounting for 26% of total UK greenhouse gas emissions (residence basis). The second highest emitter was the energy sector, rising 7% to reach 86 Mt Co2e, accounting for 17% of the total.

refers to this as the most significant gap in current energy policy, which, from this study's perspective, underscores a broader problem of persistent energy inefficiency in UK buildings. This highlights the urgent need for measures addressing energy efficiency in residential sectors to effectively mitigate climate change effects, battle against fuel poverty, and tackle growing inequality.

This study asserts that the current climate energy policy framework[11] must prioritise reducing energy demand due to inefficient usage. This could be achieved, for instance, through a competent retrofitting policy[12]. As these considerations indicate, committing to substantial and realistic improvements in energy efficiency in line with net zero strategies would contribute to a safer, greener, and fairer future for all. Failing to meet this commitment could jeopardise hunamity's survival, as several tipping points may already have been crossed or are on the brink of being crossed[13].

In this context, place-based studies investigating the existence of patterns of a persistent EEG are pivotal in providing empirical evidence that complements government plans to align energy security strategies and net zero growth plans in a fair and inclusive manner. In this connection, the objective of this paper is twofold. Primarily, this paper aims to provide the first empirical evidence regarding the existence of persistent pockets of the energy efficiency gap across UK regions. By explicitly acknowledging the presence of such pockets and identifying their specific locations, national, regional, and local governments can tailor their long-term energy plans to meet actual needs on a case-by-case basis, rather than relying on broad macro one-size-fits-all approaches, as seen in current energy efficiency policies[14]. The paper's second objective is to provide empirical evidence of potential cross-sectional heterogeneity that helps to explain the persistence of the energy efficiency gap. This supplementary analysis is crucial since both, adjustment measures undertaken to close the energy efficiency gap and patterns of persistence may contain individual-specific components, likely leading to regional variations. From an empirical perspective, this study examines the conditional persistence of the energy efficiency gap (or speed of adjustment — SOA) by considering various observable cross-sectional factors. These include general region characteristics (e.g., population and density), broader proxies for structural constraints (e.g., construction period), and selected socioeconomic conditions attributes. Incorporating these cross-sectional factors is crucial as they encompass not only fundamental determinants of the EEG but also residents' capacity to close their own EEGs, offering insights into potential opportunities and challenges for policies blending energy security and net zero growth plans.

This analysis is distinct in two aspects: its subject of investigation and the methodology employed. Firstly, regarding the subject of investigation, to the author's knowledge, this is the first empirical analysis that provides robust evidence regarding the existence of a regional persistence of the EEG across England and Wales. Earlier empirical studies have primarily aimed to identify determinants of energy ratings and energy efficiency levels (e.g., Fuerst et al., 2015; Levinson, 2016 Comerford et al., 2018; Taruttis and Weber, 2022); energy consumption patterns (e.g., Allcott and Rogers, 2014; Hahn and Metcalfe, 2021), and efficiency levels of domestic appliances (e.g., Hausman, 1979; Cohen et al., 2017; Goeschl, 2019; Boomhower and Davis, 2020). In doing so, these studies often assumed that current energy consumption is independent of past consumption levels, which, in reality, are influenced by the degree of EEG persistence. Secondly, concerning methodology, to the author's knowledge, this is the first empirical analysis that adopts the dynamic panel fractional (DPF) variable estimator developed by Elsas and Florysiak (2011, 2015). This method is applied to an initial sample of 18,361,088 domestic buildings across England and Wales[15] to investigate persistent patterns of EEG. The DPF estimator addresses econometric challenges tied to the accurate estimation of the SOA.

While much of the existing empirical literature relies on panel methods to estimate dynamic partial adjustment models (see e.g., Paul et al., 2009, Yin et al., 2016), commonly applied estimators suffer from bias due to the presence of the lagged dependent variable on the right-hand side of the specification (see Cave et al., 2023). Additionally, the risk of obtaining spurious estimations is further exacerbated when the variable of interest — in this case, EEG, is fractional in nature (bounded between zero and one). The widely used estimators were designed for continuous, unbounded dependent variables, failing to account for the fractional nature of the dependent variable and leading to biased estimates of the autoregressive coefficient (Loudermilk, 2007). The DPF estimator, as demonstrated by Iliev and Welch (2010), via parametric and non-parametric simulation approaches, consistently delivers unique results, unlike other commonly used estimators prone to non-unique outcomes at varying levels of the true SOA. Considering the nature of this study and the bias implications on both average and EEG persistence estimates, the adoption of the DPF estimator guarantees solid, unbiased cross-sectional empirical evidence regarding EEG existence and factors influencing residents' ability to promptly address their EEGs.

The robustness of these findings has been verified using the quasi-maximum likelihood (QML) estimator of Hsiao et al. (2002), one of the most accurate estimators accounting for the presence of the lagged dependent variable among regressors in a dynamic panel context. The closest paper to this analysis in terms of methodology is (Cheng et al., 2020), which employs a dynamic quantile partial adjustment of energy demand. However, like many existing papers in the field, Cheng et al. (2020) focused on investigating the heterogenous effect of drivers on energy demand, overlooking issues related to the existence of EEGs.

Significantly, this study finds that the EEG exhibits an average high degree of persistence (slow SOA) of nearly 50%, a finding that is statistically and economically significant across all Lower-layer Super Output Areas (LSOAs) in England and Wales. This finding holds significant and far-reaching implications. For instance, in the event of an energy price shock, the average resident in an average LSOA would be unable to make significant adjustments to their energy efficiency ratings for at least two years (or a half-life of 1.02 years). Given the prevailing cost of living crisis, residents' inability to timely adjust their energy efficiency ratings could expose them to continuously soaring energy bills and financial hardships, hindering their ability to take meaningful actions against inflationary pressures caused by high energy costs. From a macro perspective, difficulties in adjusting energy efficiency ratings

[11] The UK Government, guided by the UK's independent Climate Change Committee (CCC, 2020; 2022b) has recognised the significance of improving energy efficiency across different sectors, including buildings, transport, and industry. In doing so it has introduced a range of policies and initiatives aimed to encourage energy-efficient practices, reduce energy demand, and lower greenhouse gas emissions. For further detail see BEIS, 2022b; 2022a; 2021a.

[12] See Morgan et al., 2023; zu Ermgassen et al., 2022; and House of Commons Environmental Audit Committee, 2019, for further details regarding a competent retrofitting policy

[13] A tipping point is a critical threshold beyond which a system reorganises, often abruptly and/or irreversibly and a tipping element is an Earth system component that is susceptible to a tipping point. Key tipping elements include the collapse of the West Antarctic and Greenland Ice Sheets, the melting of the Arctic Permafrost, the collapse of the Atlantic Meridional Overturning Circulation, and the dieback of the Amazon Forest. See OECD (2022) for a review of the state of knowledge on how the crossing of climate system tipping points may lead the climate to change regionally or globally, both by substantially affecting the Earth system and as a result of tipping cascades, leading to potentially catastrophic impacts. Tipping points' impacts have also the potential to cascade through socio-economic and ecological systems over timeframes that are short enough to defy the ability and capacity of human societies to adapt, leading to severe effects on human and natural systems.

[14] For further details see DESNZ (2023a).

[15] See Table 1 for a detailed illustration of the regions and sub-regions included in the sample.

could rapidly escalate into more intricate and long-lasting socioeconomic and environmental issues without appropriate energy policy interventions. Thus, this study underscores the pressing need for policymakers to address the challenges posed by persistent EEG patterns and to implement targeted interventions promoting energy efficiency in line with net-zero goals.

The contribution of this investigation, which covers over 97% of the total LSOAs in England and Wales, is twofold. First, it enriches the scarce empirical academic literature on persistent EEG patterns. Second, it provides crucial empirical evidence regarding heterogeneous factors that influence the persistence of the EEG. These insights are invaluable for energy policy, environmental, and regional economics, highlighting the need for rational placed-based policy interventions overcoming energy efficiency barriers and fostering the reduction of EEG pockets across regions. Lower EEGs could subsequently reduce energy security risks while propelling the transition towards a greener, fairer, and more sustainable regional economic development. Such that, this study's findings could be used by policymakers when designing place-based policies aimed to improve the energy efficiency of domestic dwellings across LSOAs. For instance, initiatives that foster retrofitting policies (see Sowter, 2020). Furthermore, as the UK aspires to become a global leader in green energy and leverage this leadership to influence international energy decarbonisation, the findings of this investigation and ensuing policy recommendations serve as a viable test for future studies set in different international contexts.

The paper proceeds as follows. Section 2 describes the standard partial adjustment approach used to estimate the existence of the EEG, and introduces the DPF estimator used to estimate the regional persistence of the EEG. Section 3 details the data collection and summarises the data sample. Section 4 reports the empirical results and findings. Section 5 discusses our main findings and Section 6 presents some concluding remarks.

2. Empirical approach

In times of international conflicts that disrupt the energy supply and trigger energy price shocks, governments around the world must come to terms with the effectiveness of policies implemented to reduce their energy dependency. Countries' dependency on energy can be investigated by identifying the existence of patterns of persistence in their regional energy efficiency gap (EEG) as the larger the EEG, the higher the demand for energy, which ultimately increases countries' energy dependency and their vulnerability to price energy shocks. In this section, the framework of the dynamic partial adjustment model is discussed. First, the model and estimation methodology are presented. Second, cross-sectional heterogeneity and dynamic persistence are discussed. Third, endogenous concerns are addressed and finally, the variables that influence the speed of adjustment (SOA) to the optimal EEG are introduced.

2.1. Dynamic partial adjustment approach

To investigate the existence of persistent EEGs patterns, this study focuses on the energy efficiency data from Local Small Output Areas (LSOAs) in England and Wales and adopts a dynamic panel data (DPD) model, specifically a dynamic partial adjustment model (DPA). Motivated by Lintner (1956), the DPA model uses the lagged dependent variable – here the EEG – to approximate the movements of the latter from its current position ($y_{i,t}$) towards its optimal target ($y^*_{i,t}$). The traditional DPA is specified as follows:

$$y_{i,t} - y_{i,t-1} = \lambda(y^*_{i,t} - y_{i,t-1}) + \eta_i + \upsilon_{i,t} \tag{1}$$

where $y_{i,t}$ and $y^*_{i,t}$ denote the actual (observed) and optimal (unobserved) EEG of LSOA i at time t, η_i is the time-invariant individual effect, and $\upsilon_{i,t}$ is the idiosyncratic error term. In this dynamic model, (equation (1)), the optimal EEG ($y^*_{i,t}$) can be considered a tightening or a loosening of previously adopted energy-enhancing measures. Such that, the current EEG can be considered either above or below its optimal target. This discrepancy and the consequent speed of adjustment (SOA), from the current to the optimal level, reflects the impossibility of LSOA's quick response to price energy shocks. Accordingly, in Eq. (1), the SOA is captured by the coefficient λ ($\geqq 0$ but $\leqq 1$), which represents LSOA's attempts to adjust towards their optimal EEG. From an empirical perspective, the rate of adjustment (per time period) is bounded between 0 and 1. In other terms, an estimate of $\lambda = 0$ reflects the impossibility of the LSOA quickly adjusting toward its targeted optimal EEG, and $\lambda = 1$ otherwise. For the purpose of this investigation, an estimate of $\lambda \leqq 0$ will represent the existence of patterns of high persistence of the EEG. Alternatively, an estimate of $\lambda \geqq 1$ will imply an immediate adjustment of the EEG, from its current value toward its optimal level.

The empirical obstacle of Eq. (1) is that LSOAs' optimal EEG ($y^*_{i,t}$) cannot be directly observed. This is because, the optimal and ideally immediate response to an external shock such as a price energy shock is highly dependent on a set of individual-specific characteristics ($\mathbf{X}_{i,t}$). This dependency can be best approximated as follows:

$$y^*_{i,t} = \Omega'\mathbf{X}_{i,t} + e_{i,t} \tag{2}$$

where $\mathbf{X}_{i,t}$ denotes a vector of individual-specific characteristics, Ω' represents the corresponding coefficient vector, and $e_{i,t}$ embodies the idiosyncratic error term. Specifically, this study includes three categories of LSOAs' specific controls, associated with demography (i.e., median age, population, density), socioeconomic conditions (i.e., income, unemployment, education), and structural constraints (period of construction, type of energy source, type of building). Given the nature of Eq. (2), scholars have long argued that a two-stage approach is the most intuitive method for estimating the dynamic panel model in Eq. (1). See, for instance, Holtedahl and Joutz (2004) and Silk and Joutz (1997). However, as proved by Pagan (1984), the two-stage approaches are often susceptible to the so-called "generated-regressor problem", leading to time-invariant structural coefficients (Ω'), thus invalid inference in the second-stage[16]. The inherent consequence of the above is the risk of misinterpretation of the existence of persistent EEGs patterns as well as drawing misleading insights regarding both short- and long-run dynamics of the factors that determine such persistence. Technically speaking, it would imply that LSOAs' targeted EEGs are homogeneous and time insensitive to energy price shocks. As a result, to achieve the target in the long-run, a large variety of studies (Lin et al., 1987; Alberini and Filippini, 2011; Yin et al., 2016) have started to adopt a one-stage approach, which incorporates a short-dynamic mechanism via the substitution of Eq. (2) into Eq. (1). Such substitution takes the following form:

$$y_{i,t} = (1-\lambda)y_{i,t-1} + \lambda\Omega'\mathbf{X}_{i,t} + \eta_i + \upsilon_{i,t} \tag{3}$$

where the coefficient λ stands for the speed of adjustment (SOA) toward the targeted EEG. As commonly applied in the literature, defining $\theta = 1-\lambda$ and $\beta = \lambda\Omega'$, it is possible to formalise the standard partial adjustment model as follows:

$$y_{i,t} = \theta y_{i,t-1} + \beta'\mathbf{X}_{i,t} + \eta_i + \upsilon_{i,t} \tag{4}$$

This study considers Eq. (4) as the unconditional baseline specification of the partial adjustment model, which allows for simultaneous single-stage identification of persistent EEGs patterns while avoiding concerns of valid second-stage inferences. More precisely, from Eq. (4), this paper aims to provide an answer to two main research questions. First, is there exist a pattern of persistence in the energy efficiency

[16] The two-stage approaches fail to account for suitable standard error adjustment in the second-stage, often resulting in invalid inference and over-rejection of the null hypothesis. For further reading see Kripfganz and Schwarz (2019) on the second-stage standard-error correction.

gap (EEG)? Second, if so, which are the factors that determine such persistence, and how can they counterbalance both short- and long-run negative effects of price energy shocks? The findings of this unconditional baseline specification, are reported in Table 3 presented in Section 4. In this context, short-run insights will be obtained via $\hat{\theta} = 1 - \hat{\lambda}$ estimates. Whereas, long-run intuitions will be approximated via $\hat{\Omega} = \hat{\beta}/1 - \hat{\lambda}$.

2.2. Cross-sectional heterogeneity and dynamic persistence

The estimation of the unconditional specification of the partial adjustment model used in this study (Eq. (4)) has become increasingly prominent in the empirical literature of a wide array of fields (Operational research (Lin and Kao, 2014); Trade Credit (García-Teruel and Martínez-Solano, 2010); Banking best practices (Casu and Girardone, 2010); Firms' capital structure (Flannery and Rangan, 2006; Cook and Tang, 2010); Information and communication technology (Abdurrahman et al., 2016); among others) because it allows for simultaneous single-stage estimation of the SOA while avoiding concerns of valid second-stage inferences.

However, despite the above benefits, the unconditional specification of the partial adjustment model assumes a constant and therefore homogeneous SOA for all LSOAs, estimated by mean regressions. In contrast, as noted earlier, LSOAs are subject to a variety of individual-specific factors (cross-sectional heterogeneity) that highly influence the rate (speed) at which they can adjust (respond) to price energy shocks. To embody this line of reasoning, this study extends the traditional specification of the partial adjustment model (Eq. (4)) into the framework of conditional quantile regression (i.e., LSOA clusters). This extension allows for the investigation of heterogeneous drives of the EEG as well as their associated rates of adjustment. Essentially, for all conditional regressions, this study divides the sample into cross-sectional clusters (LSOA clusters). For instance, in order to analyse the effect of specific demographic characteristics (i.e., median age) on the persistence of the EEG, this study calculates quartiles of the cross-sectional distribution of LSOA demography and uses dummy variables, t, as interactions terms in the regression to estimate different slope coefficients for each quartile. This study applied the same procedure for the other two measures of adjustment heterogeneity, namely, socioeconomic conditions (i.e., education and income), and structural constraints (construction period of the property). Consequently, the rearranged baseline specification (Eq. (4)) takes the following form:

$$y_{i,1} = (\lambda + \sum_{j=2}^{4} \rho_j N_{j,t-1}) y_{i,t-1} + \boldsymbol{\beta}' \mathbf{X}_{i,t} + \eta_i + \upsilon_{i,t} \tag{5}$$

where $\rho_j \in (0, 1)$, $N_{j,t-1}$ denotes an exogenous conditional ρ-th quantile of y on $N_{j,t-1}$, used to investigate the heterogeneous effect that a specific demographic characteristic may have on the persistence of the EEG. In particular, this study uses four potential measures of adjustment, namely, median age, education, income, and construction period of the property. In general, $\lambda(\rho) \in [0, 1]$ is a reasonable interval for a given ρ_j, where lower $\lambda(\rho_j)$ implies a highly persistent EEG (or lower SOA). In practical terms, when considering for instance income, one can identify four cases. Two of them will refer to two of the most extreme cases, i.e., LSOAs where the level of gross disposable income among their residents can be defined as extremely low or extremely high. The remaining two cases will instead refer to LSOAs in which the levels of gross disposable income are low or high. Within these heterogeneous scenarios, the conditional additive-based approach allows a more accurate identification of persistent EEGs patterns via the identification of the different SOA associated with each of the above scenarios. The findings of this conditional additive-based specification are reported in Table 4 presented in Section 4.

2.3. Empirical estimation and endogeneity concerns: The dynamic panel fractional estimator

The presence of unobservable variables, such as the LSOAs' optimal EEG ($y^*_{i,t}$), poses not only technical and empirical challenges to researchers, it also raises the likelihood of encountering various endogeneity issues. These concerns, if not properly addressed, can lead to biased estimates of the true value of the EEG's persistence (SOA), which ultimately increases the likelihood of misleading interpretations of the latter and the consequent design of inaccurate policy recommendations. This study reduces the risk of endogeneity concerns by including both LSOA- and year-specific fixed effects that account for omitted variable concerns. This study also addresses the possibility of facing other sources of endogeneity, such as reverse causality, and measurement errors. On the one side, it addresses the possibility of facing other sources of endogeneity, by including the autoregressive parameter, which helps to alleviate – in part – causality concerns (Leszczensky and Wolbring, 2022). On the other side, it accounts for measurement errors by adopting a rigorous set of cleaning rules — outlined in Section 3.1.

It is worth noting that in an attempt to overcome the above challenges while estimating the time-invariant individual effect (η_i), empirical studies have moved from traditional techniques such as the OLS estimator – which produces upward biased estimates (Baltagi, 2008) – to the fixed-effect or within-transformation (FE) estimator — which produces downward biased estimates (Nickell, 1981) of the true value of the rate of persistence of the EEG. However, as shown in Cave et al. (2023) some of the most advanced econometric techniques[17] used to estimate the SOA of the dependent variable – which in this study represents the persistence of the EEG – can also lead to spurious and misleading interpretations of the latter. In the context of this investigation, Baltagi and Nickell's findings are crucial because they provide empirical evidence regarding the pivotal role played by the econometric techniques chosen to investigate the existence of persistent EEGs patterns. This evidence is particularly relevant because it helps to better understand the direct effect that an energy price shock may have on the rate of adjustment of local communities as well as to properly identify different patterns of the EEG, which is useful for energy policymaking.

Taking on board the above issues, Arellano and Bond (1991) suggested incorporating a large number of instrument variables, so that via a series of transformations, the FD-GMM estimator will be able to produce unbias and consistent estimates of λ; and as a consequence, a more accurate estimate of the true existence of persistent EEGs patterns. However, given the nature of this investigation and the suspected existence of patterns of high persistence of the EEG, the GMM estimators risk producing a sizeable loss of variation, resulting in having limited explanatory power, an issue also known as "weak instrument problem". On this issue, Blundell and Bond (1998) have found that the FD-GMM performs poorly when: (i) the level instruments are only weakly correlated with that of the first difference; (ii) λ is highly persistent; (iii) the variance of η_i is larger than the variance of $\upsilon_{i,t}$. All conditions that characterise this investigation. To bypass these concerns, recent studies have adopted the AS-GMM estimator of Ahn and Schmidt (1995), which introduces additional non-linear moment conditions under the assumption that $\upsilon_{i,t}$ is homoskedastic and uncorrelated with $\eta_{i,t}$ and $y_{i,t}$, so that

[17] The array of estimators that fail to account for the time-invariant differences heterogeneous across regions include both traditional techniques – such as the OLS estimator and the fixed-effect or within-transformation (FE) – and more advanced methods, including the first difference-GMM (FD-GMM) of Arellano and Bond (1991); the non-linear GMM estimator (AS-GMM) of Ahn and Schmidt (1995); the least squares dummy variable corrected (LSDVC) of Kiviet (1995); the System-Generalised method moments (SYS-GMM) of Blundell and Bond (1998); the long difference instrumental variables of Hahn et al. (2007); and the lag difference four (LD4) estimator of Huang and Ritter (2009).

the additional moment conditions hold: $E[v_{i,T}\Delta v_{i,t}] = 0$, and increases the performance of the estimator. Despite the better performance of the FD-GMM and AS-GMM, their differencing approach may exacerbate the impact of measurement errors on the dependent variable (Griliches and Hausman, 1986), which given the nature of this investigation may reduce the variation of the explanatory variables as well as the statistical power of the tests (Levine et al., 2000). Blundell and Bond (1998) proposed the SYS-GMM estimator, which introduces another set of moment conditions, and conversely to the previous ones, it utilises the moment conditions associated with the level Eq. (4). Therefore, instead of removing $\eta_{i,t}$ by first differencing, they use instruments in first differences that are orthogonal to $\eta_{i,t}$. It follows that when λ is highly persistent and the variance of η_i is larger than the variance of $v_{i,t}$ – as in this study – Blundell and Bond (1998) found that by utilising a system of first difference and level, (equation (4)), the SYS-GMM estimator can largely improve the estimates produced by both the FD-GMM estimator and the AS-GMM estimator, but still, be affected by the "weak instrument problem" (Bun and Windmeijer, 2010), resulting in reductions in consistency and efficiency when the estimator uses too many instruments (Roodman, 2009).

Therefore, to ensure that the findings of this investigation and its associated policy recommendations are not driven by biased and inconsistent estimates of the autoregressive coefficient, this paper adopts a more advanced econometric method of estimation, the dynamic panel fractional dependent variable (DPF) estimator, developed by Elsas and Florysiak (2011, 2015). The DPF has been explicitly designed for dynamic panel models with a fractional dependent variable. As such, conversely, to the widely adopted system-generalised method moments (SYS-GMM) of Blundell and Bond (1998) and the least squares dummy variable corrected (LSDVC) of Kiviet (1995), the DPF is the only one capable to deal with the intricacies of a dynamic panel data model, in terms of cross-sectional heterogeneity, dependency of the autoregressive coefficient and the fractional distribution of the dependent variable (Cave et al., 2023). To exploit such advanced characteristics of the DPF estimator the sample has been divided into four quartiles. The rationale behind this choice is to be able to capture the effect of structural (age of dwellings' construction) and socioeconomic disparities (median age; education; gross disposable households' income, per capita) on patterns of regional persistence of the EEG. In doing so, the DPF estimator builds on an explicit specification of the fixed effects' distribution (see Baltagi, 2008; Loudermilk, 2007) to estimate the conditional additive-based specification reported in Eq. (5). It is worth mentioning that the DPF estimator is a doubly-censored tobit estimator (with censoring at 0 and 1), which conversely to the doubly-censored tobit estimator of Loudermilk (2007) – one that deals with the fractional and lagged dependent variable while taking care of the time-invariant individual effect by including all observations of $x_{i,t}$ in the fixed-effect specification – the DPF encompasses (Mundlak, 1978) style devices, $\bar{x}_i$, which are simply defined as $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$. In doing so, the DPF estimator incorporates initial EEGs and time averages of LSOA characteristics as determinants of the target EEG. The above incorporation allows for correlation between the regressors and the fixed-effects component, producing unbiased and consistent estimates in dynamic fractional panels while dealing with the so-called "incidental parameters problem" (Neyman and Scott, 1948)[18]. All in all the adoption of the DPF allows for the explicit account of the conditional distribution of the time-invariant individual effect, whereby η_i will depend on the mean of the regressors and the initial observation of the dependent variable, resulting in unbiased and consistent estimates.

[18] The so-called "incidental parameters problem" refers to the fact that in the dynamic panel context with a fractional and lagged dependent variable, it is not possible to separate the fixed effects (i.e. unobserved, time-invariant LSOA heterogeneity) from the maximum-likelihood estimates of the explanatory variables' coefficients through any known transformation.

2.4. Determinants of the persistence energy efficiency gap

This section provides a brief explanation of the theoretical linkages between the energy efficiency gap and some of the most relevant variables used to estimate the optimal EEG target for LSOAs. Specifically, this study focuses on four potential determinants of the persistent energy efficiency gap: the construction period of the property, education, income, and median age.

Construction period: According to statistics from the ONS (2022a), there exists a negative relationship between the year of construction and the energy efficiency of homes due to evolving building practices, materials, technology, wear, and tear. Following this rationale, older homes constructed before energy efficiency became a central concern would tend to be less energy efficient, leading to higher energy consumption, increased utility bills, and a larger carbon footprint. In contrast, homes built more recently would be the most likely to incorporate stricter energy-efficient practices and designs, minimising heat loss and reducing the need for excessive energy consumption and carbon emissions. However, empirical studies from the same source (ONS, 2022b) suggest that of the 10 areas in Britain with the highest proportion of efficient homes, eight (80%) are in the City of London. This finding contradicts the theoretical negative relationship between the year of construction and the energy efficiency of homes in the UK. In simple terms, with approximately 88% of homes being constructed prior to 2012, the city of London possesses a long-lived housing stock, and consequently, it should rank among the less efficient areas in Britain, rather than among the areas with the highest proportion of efficient homes. Unlike the ONS's suggestions that the construction period (year of construction) is the most significant factor affecting the energy efficiency of homes, this paper argues that the direction of the influence of the year of construction on energy efficiency is not clear and most importantly, that the year of construction should only be used as an indicator of energy efficiency, not as the sole determinant of the EEG. Education, income, and median age also play significant roles.

Education: There is evidence of low-energy efficiency policies failing to translate into high energy efficiency in domestic buildings (DESNZ, 2023d; ONS, 2019). This failure can be attributed to a variety of causes, including households' heterogeneous behaviour (Peng et al., 2012; Blight and Coley, 2013; Gillingham and Palmer, 2014), opaque energy-efficient policies (House of Commons Environmental Audit Committee, 2019), and/or unfocused energy-efficiency nudges (Park et al., 2023, Gillingham and Tsvetanov, 2018). Therefore, it is important to adopt a measure that accounts for such variation, allowing deviations from optimal values to be identified as natural variation. For instance, due to households' cognitive bias regarding the benefits of engaging in energy-efficient behaviours, rather than failures in policy design. According to the Opinions and Lifestyle Survey (ONS, 2021), there is a positive relationship between households' understanding of the benefits of adopting energy-efficiency measures and their decision-making to engage in energy-enhancing investments or behaviour. In simple terms, households that ignore how efficient their homes are, feel that their homes are already efficient enough, or do not understand the benefits of making their homes more energy efficient, are less likely to engage in energy-efficient behaviours. This study uses the level of education as a proxy of households' cognitive bias. Stanovich and West (2000) explained that people with high levels of cognitive ability will have the required computational ability to calculate realistic losses scenarios compared to people with low cognitive ability who are constrained by their ability to process and evaluate information due to their bounded rationality (Gerarden et al., 2017; Schleich et al., 2016). The expectation of this study is to find a negative relationship between households' cognition levels and the magnitude of the energy efficiency gap, as educating people regarding the environmental and financial losses caused by EEGs could motivate them to voluntarily engage in energy-efficient behaviours (Jia et al., 2017; Masoso and Grobler, 2010), thereby reducing both the EEG and carbon footprint while awaiting for the implementation of much more competent housing energy efficiency retrofitting policy (Morgan et al., 2023; Hamilton et al., 2013).

Income: There is a positive relationship between income and the home energy efficiency gap (Ozarisoy and Altan, 2022). Household income plays a pivotal role in influencing the energy efficiency of homes, as higher incomes often provide families with the financial capacity to invest in energy-efficient upgrades and technologies, such as better insulation, modern appliances, and renewable energy systems (ONS, 2021). These investments can lead to reduced energy consumption and lower utility bills over time (Hamilton et al., 2013). Conversely, lower-income households might find it challenging to afford these upfront costs, leading to the continued use of outdated and inefficient equipment, resulting in higher energy bills (Huaccha, 2022; Meadway and Huaccha, 2023).

Median Age: According to Opinions and Lifestyle Survey (ONS, 2021) there exists a positive relationship between occupants' age and the EEG of houses. This evidence suggests that the age of occupants can significantly impact the energy efficiency of homes due to lifestyle preferences, habits, health considerations, or knowledge about the efficiency of their homes. For instance, the proportion of people not considering improvements because they felt their home was efficient enough increases with age, rising from 13% of people aged between 16 and 29 years to 57% of those aged 70 years. This can be explained by the fact that younger occupants are often more environmentally conscious, might adopt energy-efficient practices, and be more inclined to insulate and weatherise their homes. Conversely, older occupants might have different heating and cooling preferences due to health concerns or comfort needs (Ryu et al., 2021). They might also be less inclined to adopt newer energy-saving technologies or practices due to familiarity with traditional methods or financial constraints.

3. Data and descriptive statistics

3.1. Data

To conduct the empirical analysis of the persistence of the energy efficiency gap (EEG), this study uses a collection of datasets from several sources merged to create a comprehensively unified dataset. First, data on dwellings' energy consumption, potential energy consumption, and other significant dwelling characteristics were collected from the Domestic Energy Performance Certificates (EPC) dataset published by the Department for Levelling Up, Housing and Communities (DLUHC). Demographic data were gathered from Table SAPE23DT13: Mid-2020 Population Estimates for Lower Layer Super Output Areas (LSOAs) in England and Wales, produced by the Office for National Statistics (ONS); where LSOAs reflect small areas with an average population of approximately 1500 people or 650 households. Next, the main dataset was supplemented with geographical delineation files from the ONS Postcode Directory (ONSPD), which matches dwellings' postcodes to current statutory administrative, electoral, health, and other geographies. Finally, socioeconomic measures of local income, unemployment, and level of education were obtained from the Annual Population Survey provided by Nomis (ONS). After matching the four datasets, a series of cleaning rules were followed. First, remove all dwellings with missing variable observations. Second, remove uncharacteristically large dwellings — i.e., dwellings with more than 15 rooms. Finally, to reduce the effects of outliers and spurious observations, all continuous energy variables were winsorised at the top and bottom 1%. The final sample consists of a larger cross-section dataset that hosts 18,361,088 unique dwelling observations across 34,758 (97%) LSOAs in England and Wales[19], over 12 years period (2008–2020).

3.2. Descriptive statistics

Table 2 reports the descriptive statistics of the main cross-sectional sample which includes England and Wales. In panel A, one observes that the sample has a median current energy efficiency score of 64 (100 kWh/m^2) – falling into band D of the Energy Performance (EPC) rating – and a median potential energy efficiency score of 79 (100 kWh/m^2) — falling into band C/B of the EPC rating[20]. As a result, the overall sample depicts a median EEG of 16.63 (100 kWh/m^2) with a standard deviation of 7.38. The maximum EEG stands at 74 over 100. The minimum EEG is bounded to zero but it can report negative values, which represent the potential savings in terms of energy consumption and associated cost compared to another property with a lower energy efficiency rating.

In this study, the EEG, namely the discrepancy between the level of energy efficiency that can be achieved using existing and cost-effective technologies and the actual level of energy efficiency observed in dwellings, is obtained by taking the difference between the current energy usage (in kWh/m^2) and the potential energy usage (in kWh/m^2). In practical terms, EEG reflects the additional costs (miss-saving) incurred for heating and powering the property. The gross disposable household income (GDHI), i.e., the income per capita available after taxes, has a Local authority district (LAD)-year average of £18,852 approx. compared to a maximum of £227,911, with a standard deviation of £6,337. The income data portray the large gap between the top and the bottom side of the UK household's income distribution, justifying in case it was needed its inclusion among the control variables. In terms of education, which is used as a proxy of households' attitudes to improving energy efficiency in their home due to available information regarding its benefits, at its maximum level, reflects that 40.8%, of the LSOAs population have attained some form of post-secondary or higher education.[21] Early analyses from the UK Office for National Statistics (ONS) have shown that the age of the property influences the level of energy efficiency[22]. This study includes the age of the property among the set of control variables and reports in Panel B of Table 2 the distribution of the main sample across construction periods and EPC ratings. Specifically, panel B shows that domestic dwellings built in 2012 or later are the ones with the larger proportion of high EPC scores, 1.06% (band A), 28.4% (band B), and 61.46% (band C) compared to older domestic buildings. However, despite the positive shift toward the construction of more energy-efficient domestic buildings, panel B also reveals that the housing stock across England and Wales is predominantly long-lived. Almost 60% of domestic dwellings were built between 1950–2011, around 41% were built before 1950, and only 0.01% were built in 2012 or later.

Another relevant factor that complements the investigation of the persistence of the EEG is the property type. Panel C of Table 2 illustrates that the type of housing stock across England and Wales varies quite substantially not only in terms of the age of the building but also in terms of property type. From columns (1)–(3) one can see that pre-1950 the housing stock was predominantly characterised by house-type domestic buildings (73%). Between 1950–2011 the proportion of houses

[19] Table 1 presents a detailed list of the regions and counties included in this investigation

[20] In the EPC rating, the most energy-efficient dwelling has an energy efficiency rating that falls into band A (92+ score) and the least energy-efficient dwelling falls into band G (1–20 score).

[21] Level 4 and above include all Higher education qualifications: degree (BA, BSc), higher degree (MA, PhD, PGCE), NVQ level 4 to 5, HNC, HND, RSA Higher Diploma, BTEC Higher level, professional qualifications (for example, teaching, nursing, accountancy). HNC and HND are higher education qualifications below degree level. Level 3 includes 2 or more A levels, NVQ level 3, Advanced GNVQ. Level 2 includes 5 or more GCSE, School Certification, 1 A level, 2 to 3 AS levels, NVQ level 2, Intermediate GNVQ. Level 1 includes all 1 to 4 GCSE passes, Foundation GNVQ, Basic or Essential Skills.

[22] For further references see https://www.ons.gov.uk/peoplepopulationandcommunity/housing/articles/ageofthepropertyisthebiggestsinglefactorinenergyefficiencyofhomes/2021-11-01[ONS, 2022: Age of the property is the biggest single factor in the energy efficiency of homes].

Table 1
Geography of the sample: England and Wales.
Source: The Office for National Statistics (ONS) Geography Portal.

North West (England)	**North East (England)**	**Yorkshire and the Humber**
Cheshire Cumbria Great Manchester Lancashire Merseyside	Northumberland, and Tyne and Wear Tees Valley and Durham	East Riding of Yorkshire and Northern Lincolnshire North Yorkshire South Yorkshire West Yorkshire
West Midlands (England)	**East Midlands (England)**	**East (England)**
Herefordshire, Worcestershire and War Shropshire and Staffordshire West Midlands	Derbyshire and Nottinghamshire Leicestershire, Rutland and Northamptonshire Lincolnshire	Bedfordshire and Hertfordshire East Anglia Essex
South West (England)	**South East (England)**	**London**
Cornwall and Isles of Scilly Devon Dorset Somerset Gloucestershire Wiltshire	Berkshire, Buckinghamshire and Oxfordshire Buckinghamshire Hampshire and Isle of Wight Kent Surrey, East and West Sussex	Inner London - East Inner London - West Outer London - East and North East Outer London - South Outer London - West and North West
	Wales	
East Wales	West Wales	The Valleys

Notes: England is divided into nine regions: North West, North East, Yorkshire and the Humber, West Midlands, East Midlands, East, South West, South East, and London. Each of the nine regions is further divided into counties. For example, Yorkshire and the Humber is composed of the counties of West Yorkshire, South Yorkshire, the East Riding of Yorkshire and parts of North Yorkshire and Lincolnshire. It shares borders with North East England, North West England and the East Midlands. Yorkshire and The Humber covers 15,406 square kilometres and is the fifth largest region in England. Its population of 5.481,431, with a population density of 356 people per square kilometre (Km^2), makes this region the fifth most populous region in England, according to mid-2021 population figures published by the ONS. The region contains some of the United Kingdom's largest cities, including Leeds and Bradford. Both cities have an average minimum temperature of just 5.1 °C meaning that they are both amongst the coldest cities in England. In January, the coldest month of the year in England, the average temperature in Leeds is 3 °C, compared to an average temperature of 7 °C across England.

built dropped to 54%, in favour of bungalows- and maisonettes-type of buildings (16% compared to 6% figures reported pre-1950). From 2012 onwards, flat-type domestic buildings have seen their largest increase of all time, reaching a percentage of 40% compared to more contained figures in previous periods. Columns (4)–(7) provide the breakdown of the total amount of domestic buildings by type of building (Detached, semi-detached, End- and Mid-terrace). The above data reveal a concerning structural problem, which solution is neither easy nor short-term reaching, and encourage further research into the complex relationship between the factors that may contribute to the persistence of the EEG across regions. All these aspects are thoroughly integrated into both baseline and conditional specifications of the dynamic partial adjustment model adopted here to investigate the regional persistence of the EEG.

Fig. 1 provides a snapshot of the scale of the problem in three periods of time, namely, the beginning of the investigation (2008), the middle term (2014), and the latest available data (2020). This is visually achieved via a set of choropleth maps that portray the size of the EEG per 100 kWh/m^2. This technique allows us to visually identify the spatial distribution of geographic areas with large EEGs, compared to those with low EEG. Specifically, the colour gradients show patterns of the highest (darker) and lowest (lighter) EEGs (in shades of purple). From comparing the three figures in the panel, one can immediately observe that closing the gap between optimal and targeted energy-efficient consumption of energy has become increasingly difficult over time. For instance, on the left-hand side of the panel, 2008 figures – the year in which EPC became a legal requirement in any transaction that involves buying or renting a property – show that buildings with the largest EEG were mainly concentrated in Wales, whereas in England the buildings with the largest EEG were highly dispersed across regions and more concentrated within Local Authority Districts (LAD). Data also show that in 2014 (figure in the middle of the panel) – six years after the legal introduction of EPCs – the EEG has become significantly larger in size and geographical dispersion. Specifically, it is possible to identify that while regions of the South East of England and London, have managed to reduce, in proportion, their EEGs compared to 2008 data, the rest of the regions have not only failed to close previous EEGs but they have been unable to contain the growing gap of the latter within their LADs. Finally, 2020 data – reported on the right-hand side of the panel – show more striking antithetical spatial patterns. For instance, looking at areas of Wales, East England, and South West, compared to London one can see that these regions have the highest EEGs in the majority of their LADs. In contrast, London appears to be the region where domestic buildings present the lowest EEG. To visually identify potential patterns of persistence of the EEG, the choropleths report the EEG at the LAD level. However, given that the deepening of this investigation is conducted at the Lower Layer Super Output Area (LSOA) level, the bottom of each choropleth reports the associated binned scatter plots of the floor-area-weighted average EEG at the LSOA level. From these binned scatter plots one can identify two relevant phenomena. First, the early concentration of a contained EEG. Second, the sizeable widening of the EEG both in magnitude and dispersion across the overall sample. This simple but insightful analysis provides crucial grounds for further investigation regarding the existence of patterns of regional persistence of the EEG.

4. Empirical analysis

4.1. Baseline results

Table 3 presents the baseline DPF regression results for the standard partial adjustment model (Eq. (4)). In particular, starting with column 1, Table 3 shows – as expected – that by failing to account for the time-invariant individual effect (LSOAs effect) the OLS estimator

Table 2
Descriptive statistics.

Panel A: Summary Statistics

	Unit	Observations	Mean	SD	Min	Median	Max
Energy Efficiency Gap	100 kWh/m^2	18,361,088	16.212	7.38	0	16.63	74
Current Energy Efficiency	100 kWh/m^2	18,361,088	61.564	12.47	16.00	64	100
Potential Energy Efficiency	100 kWh/m^2	18,361,088	77.744	9.54	39.00	79	100
Number of rooms	#	18,361,088	4.251	1.739	0.00	4	15
Floor area	m^2	18,361,088	86.79	141.67	0.00	78	5303
Income (GDHI pc)	£	18,361,088	18,852	6,337	10,649	17,466	227,911
Employment rate	%	18,361,088	72.92	5.88	45.4	73.3	77.2
Education rate	%	18,361,088	34.81	10.66	10.2	33.1	40.8
Median age	#	18,361,088	39.097	7.587	13.60	38.739	70.678
Population	#	18,361,088	1655.261	370.315	227	1585	17274
Density	#	18,361,088	4726.397	4503.813	2	3832	6224.253

Panel B: Distribution of Observations across Construction Periods and EPC Ratings

Construction Period	A	B	C	D	E	F	G
Pre 1950 (40.83%)	0.01%	0.38%	13.48%	46.67%	28.24%	8.34%	2.87%
1950–2011 (58.20%)	0.08%	4.78%	39.39%	41.07%	11.80%	2.38%	0.49%
2012 onwards (0.01%)	1.06%	28.40%	61.46%	8.32%	0.71%	0.05%	0.00%

Panel C: Distribution of Observations across Construction Periods and Property Types

Construction Period	(1) Bungalow*	(2) Flat	(3) House	(4) Detached	(5) Semi detached	(6) End terrace	(7) Mid terrace
Pre 1950	463,287 (6.18%)	1,581,468 (21.09%)	5,452,759 (72.73%)	1,051,009 (14.02%)	2,314,807 (30.87%)	1,097,156 (14.63%)	2,965,608 (39.55%)
1950–2011	1,716,775 (16.07%)	3,162,211 (29.59%)	5,806,441 (54.34%)	2,857,650 (26.74%)	3,346,031 (31.31%)	1,798,223 (16.83%)	2,502,445 (23.42%)
2012 onwards	165 (8.37%)	791 (40.11%)	1,016 (51.52%)	457 (23.17%)	620 (31.44%)	416 (21.10%)	479 (24.29%)

This table reports the descriptive statistics for the time series cross-section sample (2008–2020). Panel A reports the summary statistics for the main household controls. Panel B reports the distribution of the sample across construction periods and EPC ratings. Panel C displays the distribution of the sample across construction periods and property types. The Energy Efficiency Gap is defined as the difference between current house energy usage (100 kWh/m^2) and potential energy usage (100 kWh/m^2). Income represents per capita Gross disposable Households Income (GDHI). Number of rooms is the number of habitable rooms in the dwelling.

produces upwardly biased and therefore inconsistent estimates of the θ coefficients. Specifically, column 1 reports a θ coefficient of 0.642, suggesting a very slow speed of adjustment (SOA) equal to 0.358 ($1 - \lambda = 1 - 0.642$), significantly different from zero in both statistical and economic terms. Column 2 reports the results obtained from the other extreme of the spectrum. Specifically, it reports the estimates obtained via the FE estimator, which as is well-known it accounts for the time-invariant individual effect, η_i. However, as proven by Nickell (1981), when applied to dynamic models – as the one adopted here – produces downwardly biased estimates of the θ coefficients, leading to biased estimates regarding the degree of persistence of the EEG. In this specific case, the FE estimator produces a θ coefficient of 0.379, suggesting a fast speed of adjustment equal to 0.621 ($1 - \lambda = 1 - 0.379$), significantly different from zero in both statistical and economic terms. It is important to note that the above discrepancy regarding the existence or not of patterns of persistence of the EEG is not driven by cross-sectional differences between LSOAs but rather by the choice of the estimators, which account neither for the inclusion of a lagged dependent variable among the regressor nor for the dependent variable being fractional. To shed some light on the above inconclusive results, column 4 reports the estimates obtained via the dynamic panel fractional (DPF) estimator developed by Elsas and Florysiak (2011, 2015). The DPF estimator is an advanced estimator that has been explicitly designed for dynamic panel models with a fractional dependent variable, which as proved by Iliev and Welch (2010), is the only one that always leads to unique estimation results. Accordingly – as expected – taking the fractional nature of the EEG into account, the DPF estimator yields an average degree of persistence of the EEG that falls within the range of values generated by the OLS and the FE estimators.

In essence, according to the DPF estimates, the average persistence of the EEG is equal to 0.494 ($1 - \lambda = 1 - 0.506$), significantly different from zero in both statistical and economic terms. These results provide compelling and unbiased empirical evidence regarding the existence of patterns of persistence of the EEG. Notably, this study found that the EEG exhibits an average high degree of persistence (slow SOA) of almost 50%, a finding that is statistically and economically significant across all of the LSOAs in England and Wales. The robustness of these findings was verified (and reported in column 3) via the quasi-maximum likelihood (QML) estimator, which as proved by Hsiao et al. (2002) is one of the most advanced estimators that account for the presence of the lagged dependent variable among the regressor in a dynamic panel context[23]. However, as expected, while confirming the DPF results of this study in terms of consistency, the QML introduced some bias[24]. In particular, the QML estimator yielded a slightly higher magnitude of the average persistence of the EEG equal to 0.51 ($1 - \lambda = 1 - 0.490$), which is significantly different from zero, confirming the consistency of our results. For the full sample, the EEG's coefficient has a positive sign. That is, future EEG positively depends on its last (observed) value and other factors, including median age, the type of property, the type of energy used, and the period of construction.

All in all, the above results provide an estimate for the average degree of persistence of the EEG without allowing for cross-sectional heterogeneity that can help to explain potential determinants on regional pockets of persistent EEGs. To address this lack, Table 4 reports

[23] Hsiao et al. (2002) proved that the QML estimator outperforms GMM estimators by providing less biased autoregressive coefficients

[24] Chang and Dasgupta (2009), Iliev and Welch (2010) and Elsas and Florysiak (2011) showed that in a dynamic panel context, the DPF estimator is the only one capable to provide estimates that are almost perfectly aligned to those of the true speed of adjustment.

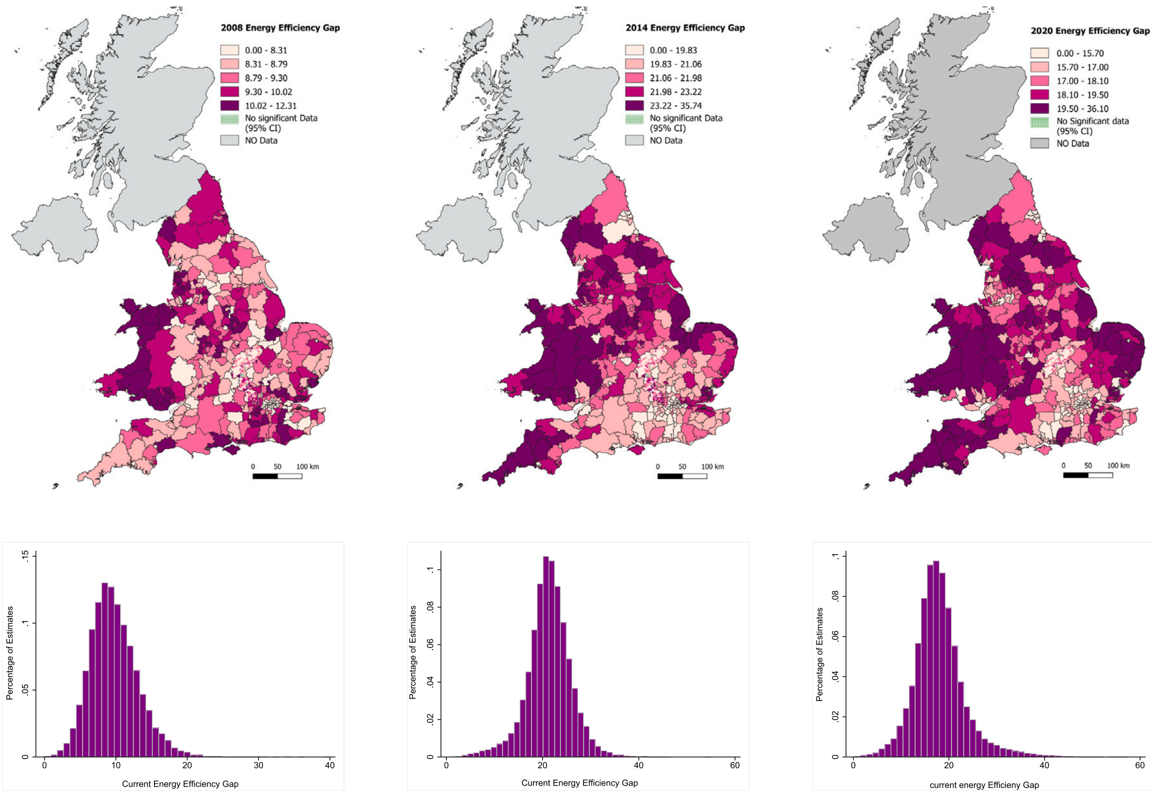

Fig. 1. Energy efficiency gap.

the results of a cross-sectional heterogeneity investigation on the persistence of the EEG divided by groups. For this purpose LSOAs have been differentiated by (i) demographic characteristics (i.e., median age), (ii) socioeconomic conditions (i.e., education and income), and (iii) structural constraints (construction period). As discussed in Section 2.4 these variables are robust determinants of energy demand, thus conditioning this empirical investigation on them will provide useful insights into the relevance of LSOAs heterogeneity for the persistence of the EEG.

4.2. Cross-sectional conditional results

Table 4 presents the results of the cross-sectional conditional investigation, showing the persistence of the EEG across LSOA clusters. In particular, Table 4 shows EEG estimates of the DPF and the QML estimator across four clusters, i.e., median age, education, income, and construction period. While the QML is known to be unbiased in the presence of a lagged dependent variable, which explains its use as a robustness test here, Chang and Dasgupta (2009), Iliev and Welch (2010) and Elsas and Florysiak (2011), proved that the latter provides inefficient results in the presence of fractional dependent variables. As a result, it can be anticipated that the QML estimates will validate the DPF estimations in terms of consistency while introducing a certain degree of bias. Table 4 shows – as expected – that most of the bias introduced by the QML estimator is due to the fractionality of the dependent variable, as the latter does not account for the fractional nature of the dependent variable. Consequently, it is not surprising to see that in all scenarios the QML estimator overestimates the SOAs, underestimating the degree of persistence of the EEG. The magnitude of the biases illustrates that a conditional analysis of SOA in the cross-section of LSOAs becomes feasible only based on an unbiased estimator, such as the DPF estimator, which is capable to deal with the four degrees of censoring considered in this analysis. That is why in what follows we will discuss the results obtained via the DPF estimator.

In particular, Table 4 shows that when the median age variable is divided into four quartiles, there is indeed some heterogeneity in the persistence of the EEG across LSOAs. Specifically, LSOAs with residents that fall into the second and third quartiles of the median distribution, exhibit a higher degree of responsiveness in adjusting their EEG compared to residents that fall into the first and fourth quartiles of the median age distribution. Consequently, both the second and third quartiles denote a lower degree of persistence of the EEG, implying that following an energy price shock those specific types of residents would be able to adjust their EEG more quickly compared to the rest of the sample - all else equal. A closer look at the LSOA education adjustment speeds suggests that heterogeneous degrees and higher degree-level qualifications or equivalents might be another reason for heterogeneity. In plain terms, LSOAs where residents are more educated exhibit systematically larger deviations from the average compared to areas populated by less educated people. In particular, the fourth quartile – LSOA with highly educated people – has the highest speed of adjustment, indicating that education is a key driver in reducing the persistence of the EEG. One will assume that this might be because, in general, areas with highly educated residents are wealthier than others. We tested for such eventuality, our results confirmed that wealthier areas are able to adjust their EEG quicker compares to the rest of the sample. However, data shows that this is true only for the wealthiest side of the distribution. On average, the effect of income on the EEG becomes crucially determinant only for extremely wealthy residents. In the majority of cases, education has a bigger effect on reducing the persistence of the EEG.

All in all our results are particularly insightful because they provide compelling unbiased empirical evidence on the energy efficiency of homes and their related EEG. Smaller EEGs are shown to be positively associated with younger informed residents. These insights can be used as additional sources of empirical data from which to support the development of competent national, regional, and local housing energy efficiency retrofit policies.

Table 3
Baseline estimates of the regional persistence of the energy efficiency gap.

	OLS (1)		FE (2)		QML (3)		DPF (4)	
$EE\ Gap_{i,t-1}$	0.642***		0.379***		0.490***		0.506***	
	(0.002)		(0.002)		(0.003)		(0.002)	
SOA	0.358		0.621		0.51		0.494	
Half-Life	1.56		0.71		0.97		1.02	
	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run
$Age_{i,t-1}$	0.023***	0.0358***	0.032***	0.0844***	0.024***	0.0489***	0.024***	0.0474***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Unemployment_{i,t-1}$	−0.005***	−0.0078***	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Education_{i,t-1}$	−0.007***	−0.0109***	−0.005***	−0.0132***	−0.005***	−0.0098***	−0.0102***	−0.0079***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$Income_{i,t-1}$	−0.012***	−0.0187***	−0.046***	−0.1214***	−0.034***	−0.0667***	−0.0694***	−0.0613***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Detached_{i,t-1}$	0.013***	0.0202***	0.017***	0.0449***	0.014***	0.0286***	0.013***	0.0257***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
$Electricity_{i,t-1}$	0.004***	0.0062***	−0.001***	−0.0026***	−0.007***	−0.0143***	−0.006***	−0.0119***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$ConstructionPeriod_{i,t-1}$	0.022***	0.0343***	−0.017***	−0.0449***	−0.028***	−0.0571***	−0.026***	−0.0514***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Year Fixed Effects	YES		YES		YES		YES	
LSOA Fixed Effects	YES		YES		YES		YES	
Number of LSOA	34,758		34,758		34,758		34,758	
Number of observations	416,959		416,959		416,959		416,959	

Notes: Table 3 presents the estimates of Eq. (4), using OLS, the Fixed Effect or Within-transformation (FE), the Quasi-maximum likelihood fixed-effect estimator, and the Data Partial Fractioned estimator. The dependent variable for columns 1–4 is the estimated Energy Efficiency Gap. Any order one autoregressive model has an exponentially declining response function to shocks measured by the half-life (HL) indicator. The HL indicator estimates the time that the process needs to close the 50% of the gap between the actual and the target position. HL is calculated as $log(0.5)/log(1-\alpha)$. All coefficients have been scaled by the standard deviation to ease interpretation. Standard errors are robust to heteroskedasticity and are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5. Discussions

A large literature argues that households do not invest in energy efficiency technologies despite it is cost-effective to do so. If this was not the case households would be able to reduce their EEGs and as a consequence, regions would be less exposed to energy shocks and climate security threats. This study argues that conversely to what has been advertised, in the UK, the so-called energy efficiency gap has not seen significant signs of improvement over the last decades. On the contrary, despite millions of pounds invested in energy efficiency policies, the regional EEGs have become larger and concentrated in specific regions. This paper provides additional empirical evidence regarding the existence of persistent EEGs pockets across regions of England and Wales, which to some extent can be explained by heterogeneity within regions. More precisely, this study has found that the magnitude of the EEG is positively influenced by the median age of residents and negatively influenced by the level of income, residents' employment status, and cognition level. In simple terms, given the existence of persistent pockets of regional EEGs, which implies high demand for energy and therefore high exposure to energy price shocks, the average resident of an average LSOA is unable to make any significant adjustment to their energy efficiency ratings for at least two years (or a half-life of 1.02 years). This situation is further exacerbated if the resident is older, not appropriately informed about the benefit of engaging in energy efficiency behaviours, and belongs to the lower side of the income distribution. The practical implications of these findings are both economically and environmentally far-reaching.

From an economic viewpoint, the existence of persistent pockets of EEGs has the potential to affect both the short- and long-run financial vulnerability of households, especially those on the lower side of the income distribution. In the short run, the surge in energy prices exposes lower-income households to higher energy bills than is expected given their financial constraints. This situation poses a significant challenge to lower-income households as they are compelled to make difficult choices regarding how to allocate their limited financial resources. For example, they must determine the portion of their disposable income that can be devoted to weekly groceries, leaving them with less to cover essential needs like electricity, heating, cooling, and almost nothing for energy-enhancing investments. This is also true in the long run when energy prices are expected to be lower. Put simply, households with larger EEGs will consistently face higher energy bills compared to similar counterparts with smaller EEGs. The higher level of energy expenditure will leave vulnerable households with less available financial resources that they can invest in improving their quality of life and development, a situation that will ultimately exacerbate their long-term vulnerability.

From an environmental perspective, considering that emissions from households – accounted for through consumer expenditure (residence basis) – are the largest contributor to total UK emissions (ONS, 2023b)[25], the existence of persistent EEGs across regions poses a threat to policies aimed at mitigating carbon emissions and the devastating effects of climate change. This is due to the fact that homes with larger EEGs have higher energy demands and consequently they emit larger amounts of greenhouse gas into the atmosphere. On these lines, the paper's estimates could be interpreted as evidence of the existence of persistent EEGs pockets and the urgent need to close them. Failure to do so will hinder any credible attempt to meet carbon budget

[25] Data from the ONS (2023), UK Environmental Accounts: Measuring the contribution of the environment to the economy, impact of economic activity on the environment, and response to environmental issues, show that in 2021, emissions related to consumer expenditure – primarily driven by heating homes and travelling – rose 7% to 135 million tonnes of carbon dioxide equivalent (Mt Co2e), accounting for 26% of total UK greenhouse gas emissions (residence basis). The second highest emitter was the energy sector, rising 7% to reach 86 Mt Co2e, accounting for 17% of the total.

Table 4
Regional persistence in the energy efficiency gap.

	Age		Education		Income		Construction period	
	QML	DPF	QML	DPF	QML	DPF	QML	DPF
EE Gap	0.536***	0.568***	0.538***	0.56***	0.573***	0.598***	0.526***	0.556***
	(−0.004)	(−0.003)	(−0.004)	(−0.002)	(−0.005)	(−0.003)	(−0.005)	(−0.003)
Interactive Terms								
EE GAP × Q2	−0.069***	−0.080***						
	(−0.002)	(−0.002)						
EE GAP × Q3	−0.071***	−0.084***						
	(−0.002)	(−0.002)						
EE GAP × Q4	−0.033***	−0.045***						
	(−0.003)	(−0.002)						
EE GAP × Q2			−0.033***	−0.039***				
			(−0.001)	(−0.001)				
EE GAP × Q3			−0.060***	−0.070***				
			(−0.002)	(−0.001)				
EE GAP × Q4			−0.090***	−0.102***				
			(−0.002)	(−0.002)				
EE GAP × Q2					−0.060***	−0.065***		
					(−0.002)	(−0.002)		
EE GAP × Q3					−0.088***	−0.095***		
					(−0.002)	(−0.002)		
EE GAP × Q4					−0.123***	−0.137***		
					(−0.003)	(−0.002)		
EE GAP × Q2							−0.025***	−0.034***
							(−0.002)	(−0.001)
EE GAP × Q3							−0.032***	−0.039***
							(−0.002)	(−0.002)
EE GAP × Q4							−0.045***	−0.051***
							(−0.003)	(−0.002)
SOA Q1	0.464	0.432	0.462	0.440	0.427	0.402	0.474	0.444
SOA Q2	0.533	0.512	0.495	0.479	0.487	0.467	0.499	0.478
SOA Q3	0.535	0.516	0.522	0.510	0.515	0.497	0.506	0.483
SOA Q4	0.497	0.477	0.552	0.542	0.550	0.539	0.519	0.495
Half-Life 1	0.90	0.83	0.90	0.84	0.81	0.76	0.93	0.85
Half-Life 2	1.10	1.04	0.99	0.94	0.96	0.91	1.00	0.94
Half-Life 3	1.11	1.05	1.07	1.03	1.04	0.99	1.02	0.95
Half-Life 4	0.99	0.94	1.17	1.13	1.16	1.12	1.06	0.99
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
LSOA Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Number of LSOA	34,758	34,758	34,758	34,758	34,758	34,758	34,758	34,758
Number of Observations	416,959	416,959	416,959	416,959	416,959	416,959	416,959	416,959

Table 4 reports the results of our cross-sectional heterogeneity investigation on the persistence of the EEG for groups of LSOAs differentiated by (i) general demographic characteristics (i.e., median age), (ii) specific socioeconomic conditions (i.e., education and income), and (iii) structural constraints (construction period). These variables are robust determinants of energy demand and conditioning on them provides useful insights into the relevance of LSOAs heterogeneity for the persistence of the EEG. The dependent variable for all LSOAs clusters is the estimated EEG.

statutory commitments and most importantly it will increase threats to humanity's survival. Along these lines, this study stresses the urgent need for competent long-term energy-climate policies that effectively address the challenges posed by the existence of persistent patterns of EEG. This is because energy security and net zero initiatives are two sides of the same coin, capable of driving the global transition to clean technologies, bringing down carbon emissions, safeguarding the environment, enhancing energy security, and realising the green growth economic opportunities offered by such a transition.

In this perspective, the long-term solution to address the UK's underlying vulnerability to international fossil fuel price volatility while fulfilling net zero commitments (carbon budgets) has been found in a clean energy transition in line with net zero goals. This paper's findings raise awareness of the fact that the challenges of meeting all four levels of security: energy security, consumer security, economic security, and climate security, as presented in the current energy-climate policy framework (DESNZ, 2023c) can be achieved via the credible implementation of a place-based energy efficiency policy that tackles the problem of persistent EEG by accounting for the heterogeneity across regions. This paper shows that problems of persistent EEGs are closely related to residents' age, income distribution, cognitive levels, and to some extent the age of the property, which is further exacerbated by the fact that the UK housing stock is among the oldest in Europe. Almost two-fifths of dwellings (39%) in the private sector were built before 1945 compared with 17% in the social sector. In contrast, more than half of dwellings (56%) in the social sector were built between 1945–1980 compared with just over a third (34%) in the private sector. These oldest properties are the most costly to retrofit for energy efficiency and to bring up to band C. Dwellings built before 1919 had the highest average cost to improve to band C, £10,861, followed by dwellings built from 1919 to 1944 (£7,226) and dwellings built after 1945 (£5,137 to £5,759) (LUHC, 2022).

In summary, drawing from the above findings, this study provides robust empirical evidence regarding two important matters: (i) the existence of patterns of persistence of the EEG across all of the LSOAs in England and Wales, and (ii) significant cross-sectional differences that can help to identify some of the most important determinants of such persistence across regions. Understanding the factors that contribute to the persistence of the EEG is important for at least two salient reasons. First, at the macroeconomic level, improving residents' energy efficiency will contribute to the reduction of energy consumption and assist a long-term transition into less energy-imported dependent economies. It will, therefore, increase countries' stability by reducing energy security risks. Second, a better understanding of the relationship between the EEG and individual-LSOAs-characteristics will provide a more accurate picture of the real needs that local areas face. These findings underscore the urgent need for policymakers to take action to promote energy efficiency and sustainability to mitigate the potential negative consequences of persistent patterns of EEG. Moreover, from an environmental perspective, addressing the persistence of the EEG is essential to reducing greenhouse-gas emissions and tackling the devastating effects of climate change.

6. Concluding remarks

The literature on the domestic energy efficiency gap is vast, yet, empirical research has largely focused on determining the magnitude of the energy efficiency gap (e.g., Hausman, 1979; Cohen et al., 2017; Allcott and Sweeney, 2017; Gerarden et al., 2017). This paper contributes to the literature by adding a place-based analysis regarding the existence of patterns of regional persistence of the energy efficiency gap in England and Wales. Specifically, using an initial large cross-sectional sample of 18,361,088 domestic dwellings, distributed across 34,758 (97%) of the LSOAs in England and Wales, this investigation provides compelling and accurate empirical evidence regarding the existence of patterns of persistence of the EEG. Notably, the study found that the EEG exhibits an average high degree of persistence (slow SOA) of almost 50%, a finding that is statistically and economically significant across all of the LSOAs in England and Wales. The paper's findings also provide additional insights into cross-sectional differences that can help to identify some of the most important determinants of such persistence across regions, highlighting the significant implications of these findings for individuals and society as a whole.

This study finds that there is compelling evidence of heterogeneity in the persistence of the EEG across LSOAs. This finding is particularly significant when it comes to determining the main driver that can be used to reduce such persistence. Specifically, a closer look at the LSOA cognition adjustment speeds suggest that, in the short run, targeted energy-enhancing nudges might help to narrow the extent of the EEGs. In plain terms, LSOAs where residents are better educated/informed exhibit systematically larger deviations from the average compared to areas populated by less educated/informed people. This finding signals that targeted energy-enhancing nudges regarding the benefit of engaging in energy-efficient behaviours or investments can make households respond more sensitively to differences in efficiency. In particular, LSOAs populated by residents with high levels of cognitive ability have the highest speed of adjustment, indicating that educating households on the benefits of engaging in energy-efficient behaviours or investments will be, in the short run, a possible solution to reduce the EEG and encourage people to voluntarily invest in energy-enhancing technologies. These results are supported by previous studies in the context of the adoption of high-efficiency technologies (Park et al., 2023; Silvi and Rosa, 2021).

6.1. Policy implications

In an era of acute inflationary pressures, skyrocketing cost of living, and climate change emergency, the findings of this study provide empirical evidence regarding the severity of the problem and the fact that in periods of economic turmoil, short-term solutions such as educating people on the benefits of engaging in energy enhancing behaviours could be a viable quicker solution to tackle the surge of energy prices and the negative consequences stemmed from it. The findings of this paper also highlight that while structural changes (such as retrofitting policies) may not be the most swiftly solution to tackling short-term imminent threats, in the long run, the deep causes underpinning the existence of persistent EEGs can be tackled only via a competent long-term energy-climate policy framework. The practical implications highlighted here are significantly relevant for policymakers. Using these insights, policymakers can encourage households to engage in energy-enhancing behaviours by targeting informative campaigns that frame the consequences of engaging in energy-enhancing behaviours as a means to avoid higher bills and the devastating effects of climate change. As proved by previous studies (Silvi and Rosa, 2021; Schleich et al., 2016; Gerarden et al., 2015), these types of campaigns have been successful in the context of consumers' behaviour. This study underscores the urgent need for policymakers to address the challenges posed by the existence of persistent patterns of EEG and to implement targeted interventions that promote energy efficiency and sustainability. The longer it would take to adjust our EEG the more difficult it would be to tackle the devastating effects of climate change. Therefore, reducing the persistence of the EEG should be a priority in achieving a safer future for all. In this spirit, our findings provide placed-based empirical evidence of energy efficiency patterns that policymakers could use while designing effective and competent place-based energy-climate policies.

6.2. Limitations

This study takes the first step to establish a large data framework that lays the foundations for a solid analysis regarding the existence of persistent patterns of EEG as well as drawing useful insights that policymakers can use while designing their energy-climate policies. The next step is to move towards quantifying the impact of energy efficiency investments in reducing the UK's EEG. This would require the construction of an even richer dataset. A dataset that allows for matching home units to individual socioeconomic conditions. As it stands this is the major limitation faced by this study. The availability of such a richer dataset would provide the opportunity for a more systematic investigation of people's behaviour conditional to their socioeconomic conditions. The granularity of such investigation would in turn allow one to reach two levels of insight. First, it would help to develop stronger and more robust foundations for studying people's needs, energy patterns, building retrofitting, and environmental challenges. Second, it would allow one to obtain evidence-based outcomes useful to design tailored policy and practice assessments for climate-energy policy.

6.3. Future research

The findings of this paper provide robust empirical evidence that can be useful for future developments in the regional energy literature. Specifically, in the regional energy literature, the autoregressive coefficient (i.e., EEG) is of central interest as future research could aim to evaluate (a) how the rate at which LSOAs adjust toward their optimal energy efficiency levels affects the level of greenhouse carbon emissions - CO_2. (b) the empirical quantification of residents' response to energy efficiency programs or framing informative campaigns. This could help to reveal whether government energy interventions are succeeding in supporting residents' capacity to close their EEGs.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2023.107042.

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