DISCUSSION PAPER SERIES

DP17990

DISTRIBUTIONAL AND CLIMATE IMPLICATIONS OF POLICY RESPONSES TO THE ENERGY CRISIS: LESSONS FROM THE UK

Thiemo Fetzer, ludovica.gazze@warwick.ac.uk and Menna Bishop

POLITICAL ECONOMY AND PUBLIC ECONOMICS

CEPR

ISSN 0265-8003

DISTRIBUTIONAL AND CLIMATE IMPLICATIONS OF POLICY RESPONSES TO THE ENERGY CRISIS: LESSONS FROM THE UK

Thiemo Fetzer, ludovica.gazze@warwick.ac.uk and Menna Bishop

Discussion Paper DP17990
Published 15 March 2023
Submitted 04 March 2023

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

DISTRIBUTIONAL AND CLIMATE IMPLICATIONS OF POLICY RESPONSES TO THE ENERGY CRISIS: LESSONS FROM THE UK

Abstract

Which households are most affected by energy price shocks and what can we learn about the incidence of carbon taxes? How large are the energy, financial, and environmental benefits of improved energy efficiency in the residential building stock? How do energy price setting policies affect incentives to invest in energy efficiency? We use granular property-level data representing more than 50% of the English and Welsh building stock to answer these questions and estimate the impact of recent energy price shocks on energy bills under different energy efficiency investments scenarios. We find that the energy price shock hits better-off regions more than poorer ones, in absolute terms. On aggregate, 30% of energy consumption, totalling GBP 10-20 billion, could be saved if buildings were upgraded to higher energy efficiency standards. Energy savings appear largely concentrated in the wealthiest parts of England and Wales. However, current policies, such as the UK's energy price cap, weaken incentives for households to invest in energy efficiency upgrades and benefit wealthier households the most. Alternative, more targeted policies are cheaper, easily implementable, and could better align incentives.

JEL Classification: Q48, C55

Keywords: Climate change, Environment, Composition of public expenditures

Thiemo Fetzer - thiemo.fetzer@gmail.com
University of Warwick and CEPR

ludovica.gazze@warwick.ac.uk - Ludovica.Gazze@warwick.ac.uk
University of Warwick

Menna Bishop - Menna.Bishop@warwick.ac.uk
University of Warwick

Distributional and climate implications of policy responses to the energy crisis: Lessons from the UK

Thiemo Fetzer Ludovica Gazze Menna Bishop *

February 27, 2023

Abstract

Which households are most affected by energy price shocks and what can we learn about the incidence of carbon taxes? How large are the energy, financial, and environmental benefits of improved energy efficiency in the residential building stock? How do energy price setting policies affect incentives to invest in energy efficiency? We use granular property-level data representing more than 50% of the English and Welsh building stock to answer these questions and estimate the impact of recent energy price shocks on energy bills under different energy efficiency investments scenarios. We find that the energy price shock hits better-off regions more than poorer ones, in absolute terms. On aggregate, 30% of energy consumption, totalling GBP 10-20 billion, could be saved if buildings were upgraded to higher energy efficiency standards. Energy savings appear largely concentrated in the wealthiest parts of England and Wales. However, current policies, such as the UK's energy price cap, weaken incentives for households to invest in energy efficiency upgrades and benefit wealthier households the most. Alternative, more targeted policies are cheaper, easily implementable, and could better align incentives.

Keywords: Energy Crisis, Economic hardship, Populism, Price cap
JEL Classification: Q48; C55

*All three authors are based at the University of Warwick. We would like to thank Arun Advani, Jane Snape, Stephanie Seavers, Sheila Kiggins, Ben Moll, Carlo Perroni, Ben Lockwood, Mirko Draca, Jakob Schneebacher, Pedro CL Souza, Lily Shevchenko, Carlo Schwarz, Mike Waterson, Lucie Gadenne, and many others for helpful comments. Reuben Collins, Leon Beaufils, Natalia Tronina, Suraj Rajesh, and Tymoteusz Gozdzik provided excellent research assistance. A previous version of this working paper was circulated under the title "How large is the energy savings potential in the UK?" We acknowledge generous funding from the 2022 Leverhulme Trust Prize in Economics and the Department of Economics and CAGE research centre at the University of Warwick.

1 Introduction

Carbon taxes, which are key to curb climate change, will increase the price of energy derived from fossil fuels. But the distributional consequences of carbon taxation are still unclear. Propelled by the post-pandemic economic recovery first, and Russia's invasion of Ukraine later (Ari et al., 2022), wholesale energy prices in Europe more than tripled in the first quarter of 2022 relative to the first quarter of 2021. Thus, this energy crisis provides a unique window into studying the economic effects of higher energy prices induced by carbon taxation. In the absence of government intervention, shocks to wholesale energy prices pass through to household energy bills, meaning price hikes can create significant welfare costs. Higher energy prices likely have heterogeneous effects across socioeconomic groups and geographies, due, at least in part, to the energy efficiency and the fuel mix of the residential building stock, as well as to households' ability to invest in energy efficiency to shield themselves from price shocks. Thus, wholesale price shocks have the potential to create differential incentives to invest in insulation and energy efficiency measures (Houde and Myers, 2021). As such, the current crisis can inform the debate on potential implications of a carbon tax in the residential building sector, which accounts for 40% of energy consumption and 36% of energy-related greenhouse gas emissions in Europe (European Union, 2021).

The United Kingdom represents an interesting context in which to study the distributional consequences of the energy crisis and the policies deployed to counter it for three reasons. First, for residential use, the UK relies disproportionally on natural gas (63%, second only to the Netherlands in Europe), while renewables and biofuels play a limited role (Figure 1). Partially due to this reliance on natural gas, UK energy prices were projected to grow even more than in other European countries, by over 600% between 2021 and 2023 (IEA, 2022). Second, the UK is among the lowest ranking European countries in terms of the energy efficiency of its residential building stock across several measures. For example, UK homes lose heat faster than in most other European countries, according to data from the company tado°.[1] Moreover, its fuel poverty rates are among the highest in Europe, standing at 12% in Wales, 13% in England, 18% in Northern Ireland and 25% in

[1]Source: `https://www.tado.com/t/en/uk-homes-losing-heat-up-to-three-times-faster-than-european-neighbours/` accessed on January 30, 2023.

Scotland (Hinson and Bolton, 2022; Guertler et al., 2015). Third, the UK – just as many other countries around the globe – has a wealth of underutilized data that enable a distributional analysis of different energy pricing policies. As such, quantifying the impact of the current energy crisis on UK households can shed light on some of the worst-case scenarios that other countries and regions might face in the transition to the decarbonisation of the residential building sector.

For this purpose, we develop a measure of energy consumption for properties in England and Wales that allows us to assess the distributional impacts of different energy price scenarios or policy interventions. First, we harness the Energy Performance Certificate (EPC) database, which includes over 22 million certificates detailing estimates of energy expenditure along with other granular public data on energy consumption. The underlying set of unique properties – around 15 million – represents a large share – at least 50% – of the English and Welsh residential building stock. Each EPC includes model-based energy consumption estimates for space heating, hot water generation, and electrical light consumption based on the physical characteristics of a particular building, a thermodynamic modelling approach, and *assumptions on occupancy*. We anchor the derived energy consumption measure with anonymized individual-level meter reading data along with granular spatial energy consumption data. This moment-matching rescaling approach allows us to capture local demographics and socio-economic characteristics that may affect energy consumption *over and above* what the model-based consumption figures can provide. This anchoring is vital to study the distributional impacts and it may serve as key input to future research. Out-of-sample validation approaches confirm the accuracy of the modelling approach.

Second, we use these energy consumption estimates to project energy bills under different price policies and energy efficiency investment scenarios. For example, we model how energy bills change for different households as a result of changes in the UK's uniform energy price cap.[2] Ours are *intention-to-treat* estimates which abstract away from variation in energy expenditure driven by differences in behaviour across households. Moreover, we leverage additional, desirable information in the EPCs on recommended energy efficiency improvements by property and estimates

[2]The energy cap sets the maximum price that energy suppliers are allowed to charge customers, and is chosen by regulator Ofgem.

of reductions in energy use if these improvements were implemented.[3] Thus, we can develop a measure of energy savings potential and price this savings potential under different policy scenarios. The difference between actual and potential energy use is the measure of exposure to the price shock that we use throughout our analysis. It captures the extent of the energy price burden relative to a hypothetical scenario in which residents upgraded their homes. This exercise allows us to quantify the hidden cost of underinvestment in energy efficiency in both monetary and physical units of energy consumption. Such a hidden cost is now highly salient given recent dislocations in energy markets.

We carry out four sets of interconnected descriptive analyses at the Middle Layer Super Output Area, of which there are 7,201 in England and Wales, to enable matching with socioeconomic data. First, we characterise which areas are, on average, more exposed to the energy price shock using a best-subset selection approach. We focus especially on two area-level characteristics: median property prices and total household income. In absolute terms, more affluent regions tend to be more exposed to the shock, likely because well-off households tend to live in bigger, older, and more energy inefficient properties.

Second, we document where the highest energy savings potential lies in England. Our findings indicate that wealthy areas not only are disproportionately exposed to the price shock, but also have larger energy saving potential. A natural question, then, is why these apparently affluent households have so far not invested in upgrading the energy efficiency of their homes. We speculate that low energy prices in the past few decades translated into low projected annual savings from these investments compared with their monetary and non-monetary costs (Adam et al., 2022). As such, it is key to assess how the government's response to the current energy crisis might further affect incentives to invest.

Third, we evaluate the energy price shock under different pricing policies: we consider both a uniform unit-price cap, which is the policy implemented by the UK government in October 2022 under a scheme known as the Energy Price Guarantee (EPG), as well as an alternative two-tier energy tariff, where an initial quantity of energy consumption is charged at a subsidised rate but consumption beyond

[3] Improvements are specific to the characteristics of each dwelling. For example, the EPC only recommends cavity wall insulation if a dwelling has an unfilled cavity wall. If a dwelling has a solid wall, the EPC may recommend solid wall insulation.

this threshold is priced at market rates. Because the energy price shock is more pronounced in affluent areas, the current uniform price cap disproportionally benefits these areas, with regressive implications considering the difference between the cap and wholesale prices has to be funded, as highlighted in Fetzer (2022). We also consider prices absent intervention during the energy crisis, that is at a higher uniform cap intended to allow moderate profits for energy suppliers, for example given wholesale energy costs. We refer to this as a market price scenario. Importantly, our methodology accounts for variation in heating system and energy efficiency performance at the property level, as well as area-specific demographic characteristics.

Fourth, we analyse how different policies affect households' incentives to invest in energy efficiency. Not surprisingly: the uniform price cap weakens energy saving incentives for higher earners living in well-off areas. In contrast, the two-tier tariff maintains similar incentives as market prices while providing more targeted relief for lower income households.

This work contributes to several strands of the literature. First, it furthers our understanding of how interventions in energy markets affect the distributional impact of the energy crisis (see e.g. Harari et al., 2022; Bhattacharjee et al., 2022; Bachmann et al., 2022; Fetzer, 2022; Ruhnau et al., 2022). A key unknown is the extent to which households can adjust their energy consumption. Labandeira et al. (2017) carry out a meta-analysis, finding a short-term elasticity of -0.21 and a long term elasticity of -0.61, with additional heterogeneity by fuel type.

Second, we contribute to research investigating the existence of an energy efficiency gap, its determinants, and implications for the targeting of policies to increase take-up of energy efficiency investments (Allcott and Greenstone, 2012; Gerarden et al., 2017; Christensen et al., 2021). Regulatory barriers may be of particular importance, especially in countries with a relatively old building stock (see e.g. Fetzer, 2023). In addition, lack of information might prevent investments. Attari et al. (2010) document important deficiencies in the American public's understanding of own energy use and of the savings associated with different activities. In contrast, Myers (2019) finds that homebuyers are attentive to changes in fuel prices. However, evidence on the existence of a 'green premium', i.e. the capitalization of energy efficiency into higher prices and rents, is mixed and crucially hinges on the level of information in the market, which can be increased through mandatory disclosure (Dalton and Fuerst, 2018; Myers, 2020; Myers et al., 2022; Guin et al., 2022). Related, Zhang et al. (2012) develop a model for archetyping UK energy consumers based on behaviour and property characteristics, while Ahlrichs et al. (2022) detect a strong correlation between energy efficiency and socioeconomic factors. Similarly, Gregório and Seixas (2017) develop an index that characterises the energy renovation capacity of a community based on socioeconomic variables, property characteristics, and energy savings potential in historic town centres. Our work shows that different pricing interventions in the market affect incentives to invest in energy efficiency for households with different socioeconomic characteristics.

In the following section, we describe how we arrive at a measure of the (likely) exposure to the energy price shock in England and Wales.

2 Developing an energy-price shock exposure measure

To model the likely exposure of a household to the energy price shock, we need to gain an understanding of baseline energy consumption. Energy consumption of household i in house p is driven by at least three factors:

$$E_{i,p} = f(\text{What}_p, \text{Who}_{i,p}, \text{How}_{i,p})$$

The What_p captures the type of property or building in which energy is consumed. The predominant sources of domestic energy use are space heating, hot water generation, room lighting, and appliances. Certain properties, all else equal, consume more energy across these uses because of their physical characteristics. For example, poorly insulated and draughty properties experience more heat loss. The second factor, $\text{Who}_{i,p}$, captures residents' characteristics, for example household size and composition. For example, different socio-economic backgrounds may imply different levels of energy demand. The third factor, $\text{How}_{i,p}$, represents people's preferences. For example, people have different perceptions as to what constitutes a comfortable indoor temperature. In addition, whereas some households run dishwashers, others do dishes by hand. Moreover, these factors may interact nonlinearly: energy demand may be structurally higher in a poorly insulated property, but even more so if its residents prefer a relatively high indoor temperature.

We start our work with a measure of energy consumption based on the What_p, i.e. the underlying characteristics of a property. We augment this exogenous measure with anonymised data on actual energy consumption at the individual property level, along with energy consumption aggregates at spatially granular levels using a moment-matching approach. In doing so, we are also able to incorporate the $\text{Who}_{i,p}$ and the $\text{How}_{i,p}$ into our measure of energy consumption, i.e. the patterns of energy consumption behaviour that exist in reality across households. This rescaling ensures that we are more likely to achieve a good simulated actual exposure measure to the energy price shock. The data generation sequence is visually described in Appendix Figure A1.

In the next sections, we describe the underlying data and the generation of energy consumption estimates.

2.1 Deriving proxy measures for energy consumption

The first step in our data construction involves deriving energy consumption measures from energy performance certificate (EPC) data. EPCs provide buyers and tenants with information on the energy efficiency rating of residential properties as well as estimates of likely energy costs. EPCs also contain recommendations of measures to improve the properties' energy efficiency, including estimates of the costs and impact on energy demand of these measures. These recommended improvements are tailored to each property, including whether it has double glazing and which type of insulation its walls permit. This information allows us to calculate a measure of *actual* and *potential* energy consumption by property. The potential measure captures an estimate of how much energy would be consumed, all else equal, if all recommended energy savings measures were implemented.

The requirement for properties to have an EPC was introduced in 2007 following the EU Directive on the energy performance of buildings (Department for Levelling Up, Housing & Communities, 2017). This requirement was initially applied just to homes for sale, but has since been extended to all domestic and commercial properties being sold, constructed, or rented (Department for Levelling Up, Housing &

Communities, 2021). EPCs for domestic and commercial buildings are available to download online from the national database of all registered EPCs.[4] In total, the database includes 22,179,913 current certificates for more than 15,621,668 unique properties across England and Wales. While we derive energy consumption measures for all certificates and the underlying properties, we focus in most exercises on slightly smaller subsets of the data that include only properties that use electricity and/or gas for space-heating and hot water generation. This amounts to 13,462,394 properties or around 51% of the English and Welsh residential building stock, as council tax data estimates the total number of residential properties at 26,328,530.

A limitation of the EPC data is that certificates are valid for 10 years, meaning properties may have undergone changes, for example via the addition of an extension or insulation, that are not reflected in their most recent certificate. A second potential concern is that the EPC data may not be representative of the entire building stock, because buildings without EPCs might differ from those with EPCs. A comparison by the ONS of the EPC data vis-a-vis the population of properties from the Valuation Office Agency (VOA) data, built for council tax purposes, suggests that the properties are very similar on observables.[5][6] In fact, naive reweighting of empirical moments from the EPC sample (multiplying aggregate metrics by a factor of two) produces aggregate energy demand values that are very similar to aggregate data. In terms of the potential energy savings, there are good reasons to believe that the properties that do not have an EPC rating may have, on average an even worse energy efficiency.[7]

The estimates of actual and potential annual energy costs included in the public EPC data are expressed in terms of GBP and not in energy units (kWh). They are provided separately for space heating, water heating, and lighting. The Stan-

[4] Data are available here https://epc.opendatacommunities.org/.

[5] See Office of National Statistics, Energy efficiency of housing in England and Wales: 2021, https://www.ons.gov.uk/peoplepopulationandcommunity/housing/articles/energyefficiencyofhousinginenglandandwales/2021.

[6] Still, Department for Business, Energy & Industrial Strategy (2020) suggests that that the EPC database under-represents medium-sized properties and bungalows and over-represents smaller properties and flats.

[7] This assertion is based on data suggesting that known energy efficiency measures produce larger energy savings among properties without an EPC certificate. See BEIS National Energy Efficiency Data-Framework (NEED): impact of measures data tables 2021, https://www.gov.uk/government/statistics/national-energy-efficiency-data-framework-need-impact-of-measures-data-tables-2021.

dard Assessment Procedure (SAP) sets out the methodology used to produce these estimates (BRE, 2014). We combine these estimates with price data to back out estimated energy consumption in kWh for space heating, water heating, and lighting, reverse-engineering the SAP calculations.[8]

This process yields a vector of two energy demand proxies measured in kWh for each property p. We detail the technical approach in Appendix A and refine these measures further in the next section.

$$E^{EPC}_{p,act} = \{S_{p,act}, W_{p,act}, V_{p,act}\}$$

$$E^{EPC}_{p,pot} = \{S_{p,pot}, W_{p,pot}, V_{p,pot}\}$$

These capture the `act`ual modelled energy demand and `pot`ential demand if properties were upgraded to their highest energy efficiency potential, respectively. The three main energy use functions that are modelled are for space heating (S), hot water generation (W), and electricity use for lighting (V).

These breakdowns allow us to model energy bills as a function of the fuel used for each energy use type. For example, homes heated via electricity will face different bills than those heated via gas. Note that these forms of energy use exclude the running of appliances like TVs, computers, cookers, washing machines, or dishwashers. The predominant driver of combined modelled energy consumption is space-heating. Moreover, a natural mismatch between energy consumption across properties and the EPC-derived measures of consumption can arise because properties are not inhabited by the number of people that are assumed in the model used to produce the underlying EPC data. For example, a two bedroom house is assumed to be inhabited by more than one person. If, in fact, the property is only inhabited by one person, it might have lower energy consumption than what we would naively estimate.

We next describe how we refine and rescale the $E^{EPC}_{p,act}$ measure to match with other observed data on energy consumption.

[8]The Department for Business, Energy and Industrial Strategy (BEIS) publishes data on average gas and electricity prices for 2010-2021. Data are available here `https://www.gov.uk/government/statistical-data-sets/annual-domestic-energy-price-statistics`.

2.2 Percentile-based rescaling

We refine the EPC-derived measures using two percentile matching-based rescaling approaches. We leverage two sources of energy consumption data derived from meter readings. By doing so, we are able to anchor $E^{EPC}_{p,act}$ and $E^{EPC}_{p,pot}$ in data reflecting *who* lives in property p and *how* they live, which affect energy demand but are missing from our EPC-derived hypothetical consumption measures.

Anonomized individual property level consumption data. The first approach leverages anonymized energy data collected through the UK's National Energy Efficiency Data Framework (NEED). This dataset includes gas and electricity meter reading data for 4 million properties. The sample is designed to be representative of domestic properties in England and Wales.[9] The NEED data also include a range of property and area-level characteristics, such as property age and region, which can also be found in the EPC data, allowing for matching.

We rescale the EPC-derived energy consumption measures using these meter reading-based energy consumption data based on the distribution of energy consumption in each source. In other words, we rescale consumption estimates for properties in the EPC data in a given percentile of EPC-derived energy consumption using the consumption estimates for properties in the same percentile of NEED-derived energy consumption. We do this separately for properties with different characteristics. While this first rescaling allows us to account for variation in real consumption behaviour driven by property characteristics, it may still exclude variation driven by local demographics. To incorporate the latter information, we employ a second rescaling method.

Local area consumption data. BEIS publishes energy consumption data down to the postcode level, excluding only postcodes that include fewer than five readings. The data include both mean and median consumption for electricity and gas.[10] We repeat the moment-matching approach described above, rescaling both the EPC and

[9] The data are available on `https://www.gov.uk/government/statistics/national-energy-efficiency-data-framework-need-anonymised-data-2021`.

[10] The data are available for electricity at `https://www.gov.uk/government/collections/sub-national-electricity-consumption-data` and for natural gas at `https://www.gov.uk/government/collections/sub-national-gas-consumption-data`.

EPC-NEED augmented measures using the mean and median energy consumption values that correspond to a property's postcode.

Appendix B describes this process in more detail. Importantly, we rescale both the EPC-derived `actual` modelled energy demand and `potential` energy demand. This process leaves us with four measures proxying actual and potential energy demand at the individual property p level:

$$\mathbf{E_{p,act}} = (E^{EPC}_{p,act}, E^{NEED}_{p,act}, E^{Local}_{p,act}, E^{EPC,NEED,Local}_{p,act})$$

$$\mathbf{E_{p,pot}} = (E^{EPC}_{p,pot}, E^{NEED}_{p,pot}, E^{Local}_{p,pot}, E^{EPC,NEED,Local}_{p,pot})$$

We break down each measure into space heating, water heating, and lighting. Again, it is worth reiterating that space heating is the dominant factor in domestic energy use. For most of the analysis, we will leverage simple *ensemble* average measures, $E^{ensemble}_{p,act}$ and $E^{ensemble}_{p,pot}$, which are the unweighted average of each of the respective four measures. Figure 2 presents the resulting patterns of energy savings potential across England and Wales. This is measured as the ratio of $E^{ensemble}_{p,pot}$, potential energy demand, to $E^{ensemble}_{p,act}$, actual energy demand. Patterns of savings potential vary by energy use type. For example, areas of London have relatively high energy savings potential in space heating and lighting but relatively low savings potential for hot water.

In the next section, we provide evidence on how rescaling affects the goodness-of-fit of our estimates with respect to real consumption data.

2.3 Illustrating the goodness-of-fit of estimated consumption

We next describe how our derived property-level consumption measures fit actual energy consumption available at the MSOA level, while Section 2.4 presents a validation exercise. In Figure 3 we plot the *ensemble* EPC-derived median energy consumption measure $E^{ensemble}_{p,act}$ against MSOA-level medians. While the fit is very good, we note a mechanic underestimation of total energy consumption by our EPC-derived estimates. This underestimation can be explained by the fact that the EPC data covers only around 50-60% of properties. Appendix Figure A2 shows the goodness-of-fit of the underlying measures, highlighting that the crude $E^{EPC}_{p,act}$ measure does a decent job at fitting the data but harnessing data on energy consumption improves the goodness-of-fit substantially.[11]

Figure 4 sheds light on how the goodness-of-fit of various moments of the imputed consumption distribution varies as a function of the coverage of the EPC data relative to MSOA building stock. It displays the R^2 of a set of regressions using MSOA-level energy consumption data: mean, median and total energy consumption against corresponding moments from our *ensemble* consumption measure $E^{ensemble}_{p,act}$. Not surprisingly, the goodness-of-fit is quite low when we restrict our sample to areas where the EPC data cover only a small fraction of the residential housing stock. The fit improves rapidly as the data gets more representative. Appendix Figure A3 further emphasises that rescaling improves goodness-of-fit across each of the three moments that we consider.

Interestingly, the goodness-of-fit appears to peak at around 75% across our four energy consumption measures. In Appendix E we find a similar maximal goodness-of-fit when trying to explain variation in actual individual property-level energy consumption data even including property fixed effects. This result suggests that the unexplained variation might be due to time-varying characteristics of who and how people live in a property. This unexplained variation can explain, at least partially, the difference between the engineering estimates of the benefits of energy efficiency investments and smart technologies and estimates based on actual energy use (Brandon et al., 2022).

We next consider an additional out-of-sample validation exercise comparing empirical moments that were not used in the training step.

2.4 Out-of-sample validation comparing empirical moments

For some local authorities, we have data that provide pairwise measures of both the mean and median electricity and gas consumption by district and by property-type and floor-area band.[12] We did not use these data in the rescaling as it is coarser

[11] Appendix Figures A4 and A5 present corresponding scatterplots for estimates of average and total energy consumption at the MSOA-level respectively.

[12] Local authority table, England and Wales, `https://www.gov.uk/government/statistics/national-energy-efficiency-data-framework-need-consumption-data-tables-2021`.

than postcode-level data. We can therefore use these measures in an out-of-sample validation exercise.

We do so by estimating

$$E_{d,c}^{BEIS} = \alpha + \beta \times E_{d,c,act}^{ensemble} + x_{d,p} \times \nu + \epsilon_d$$

where $E_{d,c}^{BEIS}$ stands for the median or mean energy consumption of a property with a characteristic c in district d, that is, these are derived moments in the actual energy consumption data. We construct the corresponding moment in aggregated form, either the median or mean, at the district by property characteristic based on the property-level *ensemble* measure: $E_{d,c,act}^{ensemble}$. We control for property-level controls and district fixed effects, $x_{d,p}$.

Our attention will be on the estimated coefficient β. In the regressions that exclude other control variables or shifters, this coefficient should be close to one if there was a near one-to-one mapping of the EPC-derived consumption measures and the actually observed consumption data. A second focus will be on the combined R^2 of these regressions. We would hope this R^2 is close to one which would indicate that, on average, our approach to measure hypothetical consumption captures the variation in actual consumption quite well.

Lastly, we are interested in whether, after absorbing district fixed effects and property characteristics included in the vector $x_{d,p}$, our EPC-derived consumption measure $E_{d,c,act}^{j}$ carries signal over and above area- and property characteristic-specific idiosyncrasies. In other words, this exercise tests whether our two-way rescaling approach achieves its goal.

Unconditional fit. In Figure 5 we present the simple unconditional scatterplot of the two datasets. On the horizontal axis we plot the EPC-derived median energy ensemble predicted energy consumption at the district by floor area combination level in Panel A, and the district by property type level in Panel B, $E_{d,c,act}^{ensemble}$. The vertical axis plots the actual observed median consumption for 2019, $E_{d,c}^{BEIS}$.

We observe a tight fit even in the unconditional regressions. We next explore this validation more systematically.

Conditional fit. We first compare the BEIS empirical moments of the median and the mean electricity and gas consumption with the five measures we construct based on the EPC measures. Table 1 presents these results, adding control variables across panels. Based on the patterns in this table, we conclude that our empirical approach calibrates the EPC-derived data to actual consumption data well, which allows us to provide a richer view of the likely impact of the energy price shock. A similar picture emerges when studying the district-by-property-type empirical moments presented in Appendix Table A1. We next describe how we use the energy consumption estimates to arrive at estimates of energy bills under different policy and price scenarios.

2.5 Estimating energy bills

With the above vectors of energy demand proxies broken down by respective energy use functions, along with information on which fuels are used to heat properties and the appropriate energy tariff, we can derive estimates of household energy bills under the following price and policy scenarios.

1. Historical energy price cap. In January 2019, the UK regulator, Ofgem, adopted a uniform energy cap, that is a maximum price that energy suppliers are allowed to charge customers for gas and electricity. This cap reflects the costs of supplying energy and allows modest profits (Ofgem, 2022a). The cap has been updated every 6 months until October 2022, when it started to be updated on a quarterly basis. The price cap was originally conceived to protect inattentive consumers from being charged unfair rates. In its early years, some energy contracts on the market were cheaper than the cap, but since the summer of 2021, the cap has been the cheapest rate available. This phenomenon is due to price increases between the time at which the price cap is set and the time at which it comes into effect (Ofgem, 2022b).[13] As such, the cap has been a more accurate reflection of the prices faced by households in 2022 than in previous years. Our study incorporates price cap values from October 2021 and October 2022.

[13] As of October 2022, this gap has been shortened from two months to 25 working days.

2. Energy Price Guarantee (EPG). In September 2022, the UK government announced the Energy Price Guarantee (EPG) programme as a response to the ongoing energy crisis. Another form of uniform price cap, the EPG reduces the maximum per unit rate below the level of the October 2022 price cap in an attempt to limit the average household energy bill to around £2,500. As discussed in Fetzer (2022), the standing charge is maintained at the level of the October 2022 price cap.

3. Two-tier tariff. As an alternative policy proposal to the EPG, discussed in more detail in Fetzer (2022), we consider a two-tier tariff such that the standing charge is fixed at the level of the October 2021 price cap, as are unit prices for the first 9,500 kWh of natural gas consumption and the first 2,500 kWh of electricity consumption. As 50% of UK households consume less than 12,100 kWh of natural gas and 2,900 kWh of electricity, this would drastically limit energy price increases for the bulk of households.[14] We consider a second tier unit price of 20 pence per kWh for natural gas and 60 pence per kWh for electricity, which, together with the first tier described above, would have a similar cost to the government as the EPG. This tariff would offer much more targeted support without undermining the incentive to save energy created by higher unit prices.

For our property-level energy consumption estimates $\mathbf{E_{p,act}}$ and $\mathbf{E_{p,pot}}$, we are therefore able to produce vectors of spending estimates. For example, for the preferred ensemble average energy consumption estimate $E^{ensemble}_{p,act}$, we produce the following four spending estimates that use the October 2021, October 2022, EPG and Two-tier tariff scenarios, respectively:

$$\mathbf{C}^{ensemble}_{p,act} = (C^{ensemble}_{p,act,21}, C^{ensemble}_{p,act,22}, C^{ensemble}_{p,act,EPG}, C^{ensemble}_{p,act,Two-tier})$$

These estimates allow us to measure changes in energy bills under different price scenarios and policy interventions at the individual property-level. We next carry out a distributional analysis under different price scenarios using data aggregated to the MSOA-level to characterise how these measures affect households with

[14] See https://www.gov.uk/government/statistics/national-energy-efficiency-data-framework-need-consumption-data-tables-2021.

different characteristics.

3 Empirical analysis

Our empirical analysis aims to answer four questions:

1. Where will the energy price shock hit the hardest?
2. Where is energy savings potential the highest?
3. Which places stand to benefit most from the two policy alternatives considered (EPG vis-a-vis two-tier tariff)?
4. How does policy affect energy savings investment incentives?

Due to data limitations, our analysis focuses on properties in England and employs aggregate data. In what follows, we use the *ensemble* measure of energy bills and simplify the notation such that $C^{ensemble}_{p,act,j} = C^{j}_{p,act}$ and $C^{ensemble}_{p,pot,j} = C^{j}_{p,pot}$ for each price scenario indicated by superscript j.

3.1 Where will the energy price shock hit the hardest?

We begin by statistically characterising which areas in England would have been hardest hit by the energy price shock absent policy intervention. In this counterfactual world, consumers would have faced significantly higher unit prices for energy as determined by the relatively high uniform price cap announced by Ofgem in 2022. We compute the increase in the energy bills between the October 2021 to the October 2022 price cap for each property p using *actual* estimated consumption as:

$$\Delta C^{22-21}_{p,act} = C^{22}_{p,act} - C^{21}_{p,act} \tag{1}$$

We then consider a vector of socio-economic variables and perform best-subset selection (BSS), a machine learning method, to characterise which combinations of attributes have the largest explanatory power for the energy shock. This method allows us to uncover the patterns of vulnerability to the energy shock across England, a key step for understanding how to optimally design and target policies to provide relief to households. We study the following specification at the MSOA level, m:

$$\Delta C^{22-21}_{m,act} = \alpha_{d(m)} + x_m \times \beta + \epsilon_d$$

where we use the BSS algorithm to include ever more sets of control variables in x_m. Throughout, we absorb district-level fixed effects as a set of features not included in the BSS selection approach. This approach ensures that we only focus on within-district variation across MSOAs. We build features in x_m from public data sources described in more detail in Appendix F. We identify the optimal model as that which minimises the Akaike Information Criterion (AIC). The AIC measures the quality of a model by weighing up its goodness-of-fit against its simplicity, i.e. the number of features that are included in the statistical model.

Results. We present the results in Table 2. As we move across columns, the BSS algorithm introduces more variables. The order in which these are added reflects the signal carried by each variable. The first variable introduced, which is also never dropped, is median house prices: the higher the house prices in an area, the higher is the incidence of the shock. Places with an older and more educated population, with higher shares of households with more than two members (typically, families), and with more people living in fuel poverty (prior to the energy crisis) appear more exposed to the energy price shock.

In other words, the effects of the energy price shock appear stronger at both ends of the income distribution. Moreover, the shock appears less pronounced in areas with relatively high shares of social or other private rented accommodation. This is consistent with the fact that socially rented homes are typically flats or apartments, which may be more efficient than houses (ONS, 2021). Furthermore, social housing was the focus of the Decent Homes Programme, which sought to bring properties to minimum efficiency standards by 2010 (Leicester and Stoye, 2017). Our analysis thus underlines that targeting of interventions in energy markets will be key to ensuring these interventions reach the right set of households.

3.2 Where is the highest energy savings potential in England?

We next study where the highest energy savings potential is in England. To do so, we construct the difference in expected energy bills between the actual and potential energy consumption estimate derived from the EPC data, holding energy prices constant at the October 2022 uniform price cap. This measure characterizes how much lower could energy bills be if recommended energy efficiency investments were implemented, even absent further government intervention on prices. In other words, we compute:

$$\Delta C^{22}_{p,act-pot} = C^{22}_{p,act} - C^{22}_{p,pot} \tag{2}$$

Empirical specification We next want to characterise where the energy savings potential is distributed using a best-subset selection (BSS) exercise. This characterisation may cast some light on policy interventions to encourage energy savings that can alleviate the likely hardship induced by the energy price shock. The focus here is on the components that we cannot measure in the property-level data: the socio-economic makeup of the resident population. We estimate the following linear specification at the MSOA level:

$$\Delta C^{22}_{m,act-pot} = \alpha_{d(m)} + x_m \times \beta + \epsilon_d$$

where x_m measures socio-economic characteristics of the area or resident population. We also absorb district fixed effects, $\alpha_{d(m)}$.

Results. The results are presented in Table 3, which is structure like Table 2 except that the dependent variable now measures the energy savings potential, as opposed to exposure to the energy price shock. The patters that emerge are also similar. We see a first cluster where the energy savings potential appears more concentrated in areas with higher house prices and with an older and more educated demographic. This is not surprising: prior to 2021, energy was relatively cheap and hence households had little financial incentive to save energy. A second cluster of high potential savings highlights areas with high degrees of fuel poverty.

These patterns underline the importance of aligning incentives for able-to-pay households. One way to do so is by allowing market prices to signal scarcity while providing assistance to fuel-poor households. In the next section, we document that the existing policy framework does not meet these requirements.

3.3 The EPG appears untargeted

We next characterise how untargeted the EPG is and how it distorts energy saving incentives, following Fetzer (2022). The EPG introduces a wedge between consumer-facing prices and the price cap set by the Ofgem regulator. With the EPG, the increase in bills that would have arisen if energy prices had been set as per the Ofgem price cap announced in October 2022 relative to the October 2021, $\Delta C^{22-21}_{p,act}$, can be decomposed into two components. For each property p, the first component represents the increase from October 2021 bills to the energy bills faced by *consumers* under the EPG:

$$\Delta C^{EPG-21}_{p,act} = C^{EPG}_{p,act} - C^{21}_{p,act} \tag{3}$$

The second component represents the implicit subsidy that the government pays, that is the wedge between the Ofgem price cap and the EPG price:

$$\Delta C^{22-EPG}_{p,act} = C^{22}_{p,act} - C^{EPG}_{p,act} \tag{4}$$

The same decomposition can be constructed for the two-tier tariff. We compute MSOA-level averages of these metrics and then compare which socio-economic characteristics drive the underlying variation. We then characterise how the energy price shock affects different areas differently under the different policies.

Empirical specification. We estimate the following linear specification

$$\Delta C^{j}_{m,act} = \alpha_{d(m)} + x_m \times \beta + \epsilon_d \tag{5}$$

for the unmitigated shock, $j = 22 - 21$, as well as for the consumer-facing and government subsidized components of the shock under the uniform price-cap (EPG) and the two-tier tariff, $j \in \{EPG - 21, 22 - EPG, \text{Two-tier} - 21, 22 - \text{Two-tier}\}$. x_m measures socio-economic characteristics of the area that capture the relative deprivation of an MSOA. To assess the incidence of the energy price shock, we study three measures of relative deprivation: median property prices, average household income and a rank measure of income from the Indices of Multiple Deprivation. We also absorb district fixed effects, $\alpha_{d(m)}$.

Results. Figure 6 plots a binned scatterplot with the linear regression fit of bills under different price scenarios against MSOA-level house prices (Panel A) and average household income (Panel B). We consider four scenarios for bills: 2021 values, $C^{21}_{p,act}$ (black triangles), 2022 values without intervention, $C^{22}_{p,act}$ (navy circles), 2022 values under the EPG, $C^{EPG}_{p,act}$ (maroon diamonds), and 2022 values under the two-tier tariff, $C^{\text{Two-tier}}_{p,act}$ (gray squares).

In the absence of government support, bills would have increased drastically between 2021 and 2022 (the blue circles are shifted up with respect to the black triangles) and more so in high property-value and high-income MSOAs (the blue line is steeper than the gray one). The energy price guarantee shifts consumer-facing prices downwards, thereby providing relief for all households based on levels of consumption. However, owing to the fact that wealthier households consume more energy and tend to live in particularly energy-inefficient properties, the EPG disproportionately benefits better-off areas (the maroon line is slightly flatter than the blue one). Moreover, because energy prices are distorted downwards, energy saving incentives are weaker under the EPG.

In contrast, a two-tier tariff keeps the house-price and energy bill gradient nearly the same as under market prices. In other words, a two-tier tariff resembles a lump sum transfer to households that have relatively low energy consumption. The marginal price signal remains intact and in fact, is slightly steepened. As a result, energy saving incentives are maintained and this intervention appears much less regressive. Importantly, we note that this exercise is for illutration purposes only: the tiers can be adjusted to provide more support to lower-income households, and more tiers can be introduced.

Figure 7 presents the results from equation (5). First, the navy dot documents that the energy price shock is progressive in absolute terms: the exposure of the average property in our data is notably higher in areas with higher property prices and higher average income. This is not surprising as the energy price shock has a greater effect on households that consume a lot of energy – who tend to be better off. As a result, the energy price shock has a similar effect to carbon taxation.[15] Second, the red diamond illustrates that under the EPG this correlation is about halved, meaning that the EPG thereby exacerbates inequality across households in different regions. Third, the grey square shows that the two-tier tariff restores the correlation between wealth, as captured by house prices, or income and the size of the bill shock to the level that we see without government intervention. This pattern arises from the fact that the two-tier tariff is much more targeted than the EPG implicit subsidy.

Figure 8 decomposes the effects of the EPG and the two-tier tariff into a consumer-facing component and a government subsidy. The attenuation in the wealth and income gradients of the energy shock under the EPG (red diamonds) is due, not surprisingly, from an attenuation of this gradient for the consumer-facing price shock, $\Delta C_{p,act}^{EPG-21}$. Moreover, the government subsidy, $\Delta C_{p,act}^{EPG-22}$ also appears regressive in absolute terms: the government supports households that live in areas that are economically better off. By contrast, the income gradient of the consumer-facing energy price shock under the two-tier tariff is similar to that under market prices. Moreover, the government subsidy is uncorrelated to area wealth and income under the two-tier tariff due to the better individual targeting properties of this price scheme. Table A2 presents these results in table format.

3.4 How does policy affect energy savings investment incentives?

We have documented three facts. First, the energy price shock will hit the most affluent parts of England more than the least affluent parts. Second, these patterns are due to decades of inaction: the more affluent parts of England boast a building stock that is quite energy inefficient and is home to households who consume, on average, more energy because they are economically better off. Third, as a result, these households stand to benefit most from the EPG. Fourth, there exist policy alternatives, such as a variable price cap, that preserve the incentives to invest in energy efficiency otherwise provided by market prices (see Bhattacharjee et al., 2022; Bachmann et al., 2022).

[15] The evidence on whether a carbon tax is progressive or regressive is mixed and based largely on theoretical models. A notable empirical exception is Andersson and Atkinson (2020).

We next characterise how the EPG disincentivizes energy efficiency investments in different areas of England. To do so, we construct the measure of the value of the energy savings measures under the October 2022 uniform price cap

$$\Delta C^{22}_{p,act-pot} = C^{22}_{p,act} - C^{22}_{p,pot} \tag{6}$$

as well as under the EPG

$$\Delta C^{EPG}_{p,act-pot} = C^{EPG}_{p,act} - C^{EPG}_{p,pot} \tag{7}$$

and the alternative two-tier tariff

$$\Delta C^{\text{Two-tier}}_{p,act-pot} = C^{\text{Two-tier}}_{p,act} - C^{\text{Two-tier}}_{p,pot} \tag{8}$$

For each of these three price scenarios, $j \in \{22, EPG, \text{Two-tier}\}$, we regress MSOA-level averages of the value of energy savings potential on MSOA-level measures of economic affluence, absorbing district fixed effects $\alpha_{d(m)}$:

$$\Delta C^{j}_{m,act-pot} = \alpha_{d(m)} + x_m \times \beta + \epsilon_d$$

Results. Table 4 presents the results. Column 1 reiterates that energy savings potential is highest in affluent areas: the market value of energy savings increases with an area's house prices, household income, and overall income rank based on the IMD data. Column 2 shows that under the EPG, the gradient of energy savings value with respect to affluence becomes notably weaker. In other words, energy savings measures, under the EPG, provide a weaker monetary incentive for households in well-off areas as compared to a scenario with prices that are closer to market prices in Column 1. By contrast, Column 3 documents how the energy savings incentive is maintained and even strengthened by a two-tier tariff compared to what market prices would imply Column 1.

4 Conclusion

This paper develops a measurement framework that enables us to model the likely impact of the energy price shock across England and Wales. This method gives us a window into measuring the energy savings potential and quantifies the cost and benefit analysis of energy savings investments. Fetzer (2022) presents more detailed estimates.

First, we observe that the present UK policy path is quite incoherent. The EPG disproportionately benefits well-off households because 1) the reduction in the unit rate relative to market prices disproportionately benefits households with high energy consumption and 2) energy consumption increases with income. Moreover, the financial benefit of the EPG appears skewed even among high-earners. Among an estimated 280,000 households with an annual income above £150,000, around 14,000 households, representing the 95th percentile of energy consumption in this group, consumes more than twice as much energy compared to the median of all other households in this high-income group.

Second, our analysis highlights that the UK has a large and untapped energy savings potential. We estimate that England and Wales alone could save up to 29% of primary energy consumption in the residential sector through reduced electricity and natural gas consumption used for space heating and hot water generation if residential properties were upgraded to their highest energy efficiency standard – primarily through improved insulation measures. The EPG weakens incentives to invest in energy efficiency upgrades by around 30%: energy efficiency upgrade investments would save households between £10 to 16 billion per year if they had to pay current market prices for energy. The EPG lowers the prices that consumers face, as a result, energy efficiency upgrade investments under the EPG would only save households between £7 to 11 billion rendering them less economical.

Yet, energy savings investments could pay for themselves within a relatively short period of time. We estimate that boiler replacements for the properties we have EPC data for would cost around £10 billion. The insulation program would cost around £50 billion. With an interest rate of 3%, projected savings of £10 billion, and an investment volume of £60 billion for the properties for which we have EPC-based recommendations (around 50% of the building stock), we estimate that energy efficiency upgrades, in particular insulation and boiler replacement, would pay for themselves within six to seven years.

On top of permanent financial relief to households, energy efficiency upgrades would provide large environmental benefits. We estimate that the energy efficiency upgrades may save between 25 to 40 million tons of CO2 per year which, with a carbon price of £75 per ton, would provide further savings between £1.5 to £3 billion per year. Thus, it is imperative to build more evidence to understand why existing schemes have not been successful in achieving scale.

Crucially, the UK government has much of the data needed to ensure timely, targeted, and cost-effective interventions at its disposal. With these data, a broad set of alternative policies could be considered. For example, instead of a uniform price cap, the government could propose a two-tier tariff providing more generous targeted support without eroding energy savings incentives. Alternatives that provide even more targeted support with better incentive preservation may also be implementable (see Bhattacharjee et al., 2022; Bachmann et al., 2022). The two tier-tariff could be designed to have a similar costing as the government's uniform price cap but could be even more targeted.

References

Adam, Stuart, Isaac Delestre, Peter Levell, and Helen Miller, "Tax policies to help achieve net zero carbon emissions," in Carl Emmerson, Paul Johnson, and Ben Zaranko, eds., *IFS Green Budget 2021*, IFS, 2022, chapter 8, pp. 355–391.

Ahlrichs, Jakob, Simon Wenninger, Christian Wiethe, and Björn Häckel, "Impact of socio-economic factors on local energetic retrofitting needs - A data analytics approach," *Energy Policy*, 2022, *160* (February 2021).

Allcott, Hunt and Michael Greenstone, "Is there an energy efficiency gap?," *Journal of Economic perspectives*, 2012, *26* (1), 3–28.

Andersson, Julius and Giles Atkinson, "The Distributional Effects of a Carbon Tax: the Role of Income Inequality," *Centre for Climate Change Economics and Policy Working Paper 378/Grantham Research Institute on Climate Change and the Environment Working Paper 349*, 2020, *5709* (378), 1–35.

Ari, Anil, Nicolas Arregui, Simon Black, Oya Celasun, Dora Iakova, Aiko Mineshima, Victor Mylonas, Ian Parry, Iulia Teodoru, and Karlygash Zhunussova, "Surging Energy Prices in Europe in the Aftermath of the War: How to Support the Vulnerable and Speed up the Transition Away from Fossil Fuels," 2022.

Attari, Shahzeen Z., Michael L. DeKay, Cliff I. Davidson, and Wändi Bruin De Bruin, "Public perceptions of energy consumption and savings," *Proceedings of the National Academy of Sciences of the United States of America*, 2010, *107* (37), 16054–16059.

Bachmann, Rüdiger, Moritz Kuhn, Rüdiger Bachmann, David Baqaee, Christian Bayer, Moritz Kuhn, Andreas Löschel, Ben Mcwilliams, Benjamin Moll, Andreas Peichl, Karen Pittel, Moritz Schularick, and Georg Zachmann, "How it can be done," *EconTribute Working Paper*, 2022.

Bhattacharjee, Arnab, Max Mosley, and Adrian Pabst, "A ' Variable Energy Price Cap ' to Help Solve the Cost-of-Living Crisis," *NIESR Working Paper*, 2022, (September).

Brandon, Alec, Christopher M Clapp, John A List, Robert D Metcalfe, and Michael Price, "The Human Perils of Scaling Smart Technologies: Evidence from Field Experiments," Technical Report, National Bureau of Economic Research 2022.

BRE, "The Government's Standard Assessment Procedure for Energy Rating of Dwellings," Technical Report 2014.

Christensen, Peter, Paul Francisco, Erica Myers, and Mateus Souza, "Decomposing the wedge between projected and realized returns in energy efficiency programs," *The Review of Economics and Statistics*, 2021, pp. 1–46.

Dalton, Ben and Franz Fuerst, "The 'green value' proposition in real estate: A meta-analysis," *Routledge Handbook of Sustainable Real Estate*, 2018, pp. 177–200.

Department for Business, Energy & Industrial Strategy, "Evaluation of the Domestic Private Rented Sector Minimum Energy Efficiency Standard Regulations," Technical Report 2020.

Department for Levelling Up, Housing & Communities, "A guide to energy performance certificates for the marketing, sale and let of dwellings," Technical Report 2017.

_, "Energy Performance of Buildings Certificates: notes and definitions," Technical Report 2021.

European Union, "Factsheet - Energy Performance of Buildings," Dec 2021.

Fetzer, Thiemo, "The Energy Price Guarantee: what next?," *CAGE Policy Briefing*, 2022, pp. 1–24.

_, "Regulatory barriers to climate action: Evidence from Conservation Areas in England," *CAGE Working Paper*, 2023.

Gerarden, Todd D, Richard G Newell, and Robert N Stavins, "Assessing the energy-efficiency gap," *Journal of Economic Literature*, 2017, *55* (4), 1486–1525.

Gregório, Vera and Júlia Seixas, "Energy savings potential in urban rehabilitation: A spatial-based methodology applied to historic centres," *Energy and Buildings*, 2017, *152*, 11–23.

Guertler, Pedro, Jack Carrington, and Antonia Jansz, "The Cold Man of Europe–2015," 2015.

Guin, Benjamin, Perttu Korhonen, and Sidharth Moktan, "Risk differentials between green and brown assets?," *Economics Letters*, 2022, *213*, 110320.

Harari, Daniel, Brigid Francis-Devine, Paul Bolton, and Matthew Keep, "Research Briefing - Rising cost of living in the UK," *House of Commons Library*, 2022, pp. 4–5.

Hinson, Suzanna and Paul Bolton, "Fuel Poverty," May 2022.

Houde, Sébastien and Erica Myers, "Are consumers attentive to local energy costs? Evidence from the appliance market," *Journal of Public Economics*, 2021, *201*, 104480.

IEA, "Electricity Market Report - July 2022," Technical Report 2022.

Labandeira, Xavier, José M Labeaga, and Xiral López-Otero, "A meta-analysis on the price elasticity of energy demand," *Energy Policy*, mar 2017, *102*, 549–568.

Leicester, Andrew and George Stoye, "Factors Associated with the Presence of Domestic Energy Efficiency Measures in England," *Fiscal Studies*, 2017, *38* (2), 331–356.

Myers, Erica, "Are home buyers inattentive? Evidence from capitalization of energy costs," *American Economic Journal: Economic Policy*, 2019, *11* (2), 165–88.

— , "Asymmetric information in residential rental markets: Implications for the energy efficiency gap," *Journal of Public Economics*, 2020, *190*, 104251.

— , Steven Puller, Jeremy West et al., "Mandatory Energy Efficiency Disclosure in Housing Markets," *American Economic Journal: Economic Policy*, 2022, *14* (4), 453–87.

Ofgem, "Direct debits - What you need to know," Technical Report 2019.

— , "Ofgem updates price cap level and tightens up rules on suppliers," Technical Report 2022.

— , "Price cap – Decision on changes to the wholesale methodology," Technical Report 2022.

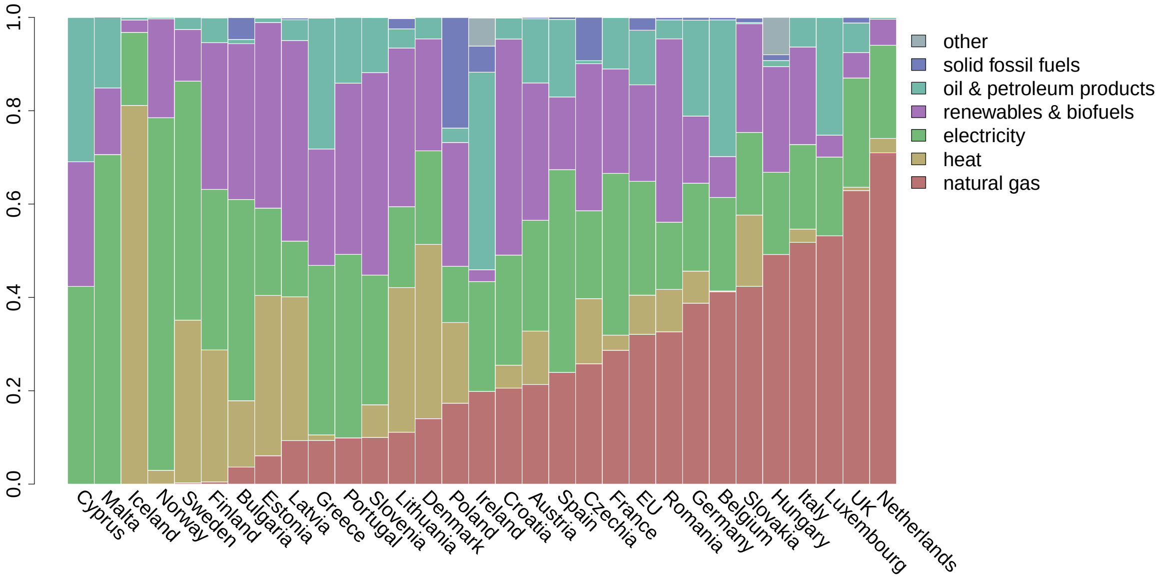
ONS, "Home People, population and community Housing Energy efficiency of housing in England and Wales Energy efficiency of housing in England and Wales: 2021," Technical Report 2021.

Ruhnau, Oliver, Clemens Stiewe, Jarusch Muessel, and Lion Hirth, "Gas demand in times of crisis: energy savings by consumer group in Germany," 2022.

Zhang, Tao, Peer Olaf Siebers, and Uwe Aickelin, "A three-dimensional model of residential energy consumer archetypes for local energy policy design in the UK," *Energy Policy*, 2012, *47*, 102–110.

Figures and tables

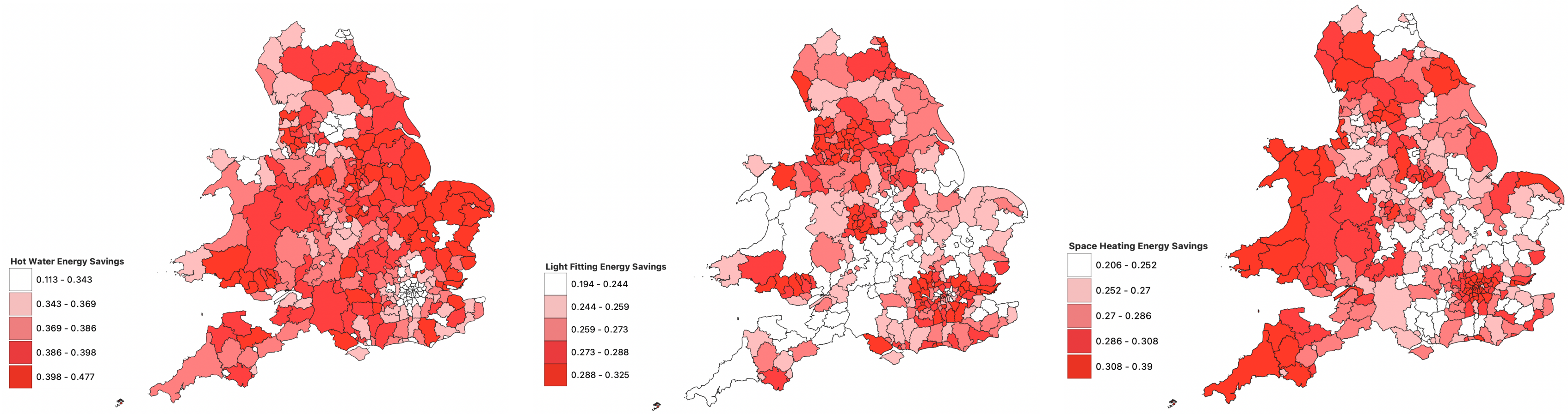
Figure 1: Share of fuels in final energy consumption across EU countries



Notes: These data are provided by Eurostat for the year 2019.

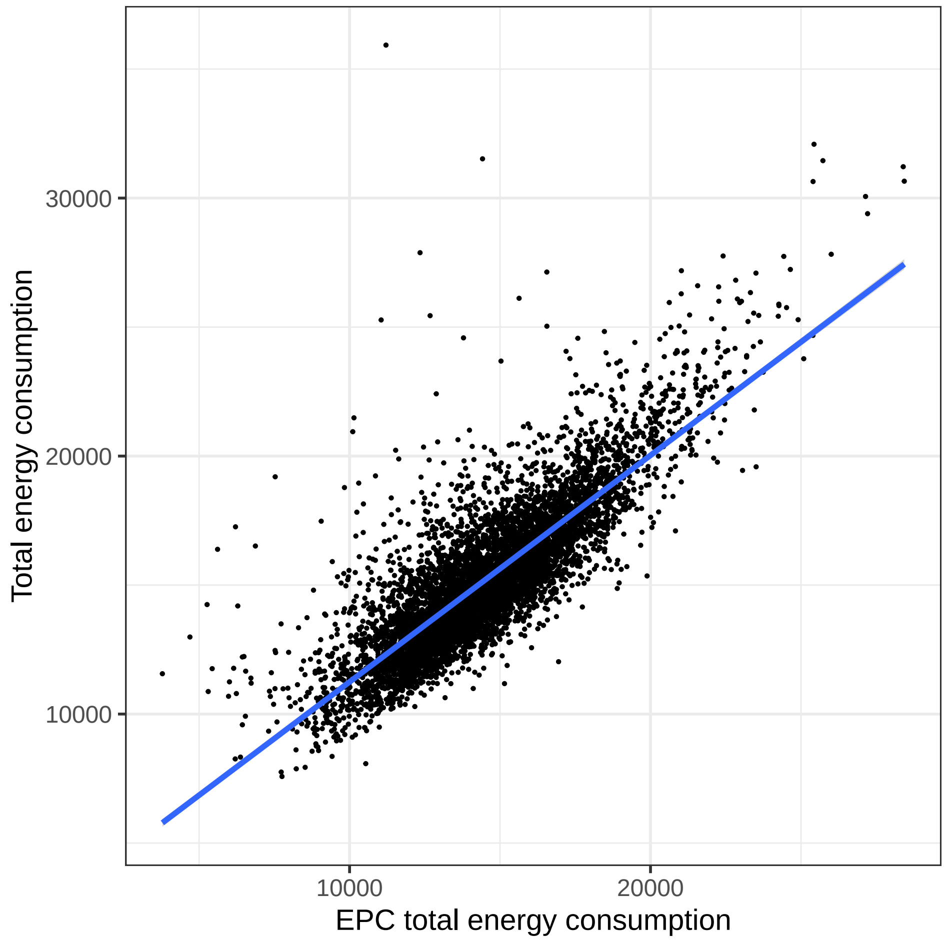
Figure 2: Energy saving potential measured in real quantities

Panel A: Hot Water   *Panel B:* Light Fittings   *Panel C:* Space Heating



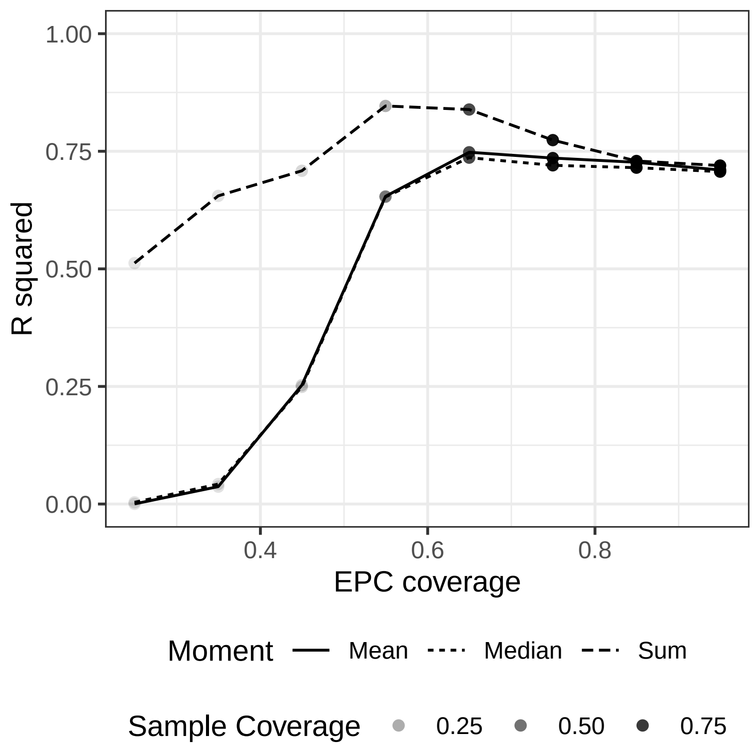
Notes: Figures present aggregate energy savings potential, measured in % of real units (kwh), that is the ratio of potential energy consumption over actual energy consumption. The higher the % the higher the gap between actual and potential consumption in relative terms.

Figure 3: Median property-level energy consumption at the MSOA-level compared with median imputed energy consumption measures from EPC-NEED data



Notes: Figures provide a scatterplot of estimates of the median energy consumption per meter from published data at the MSOA-level (for metered electricity and gas only) on the vertical axis and the median of the ensemble imputed energy consumption measure on the horizontal axis.

Figure 4: Correlation between moments of derived consumption and moments from actual consumption data

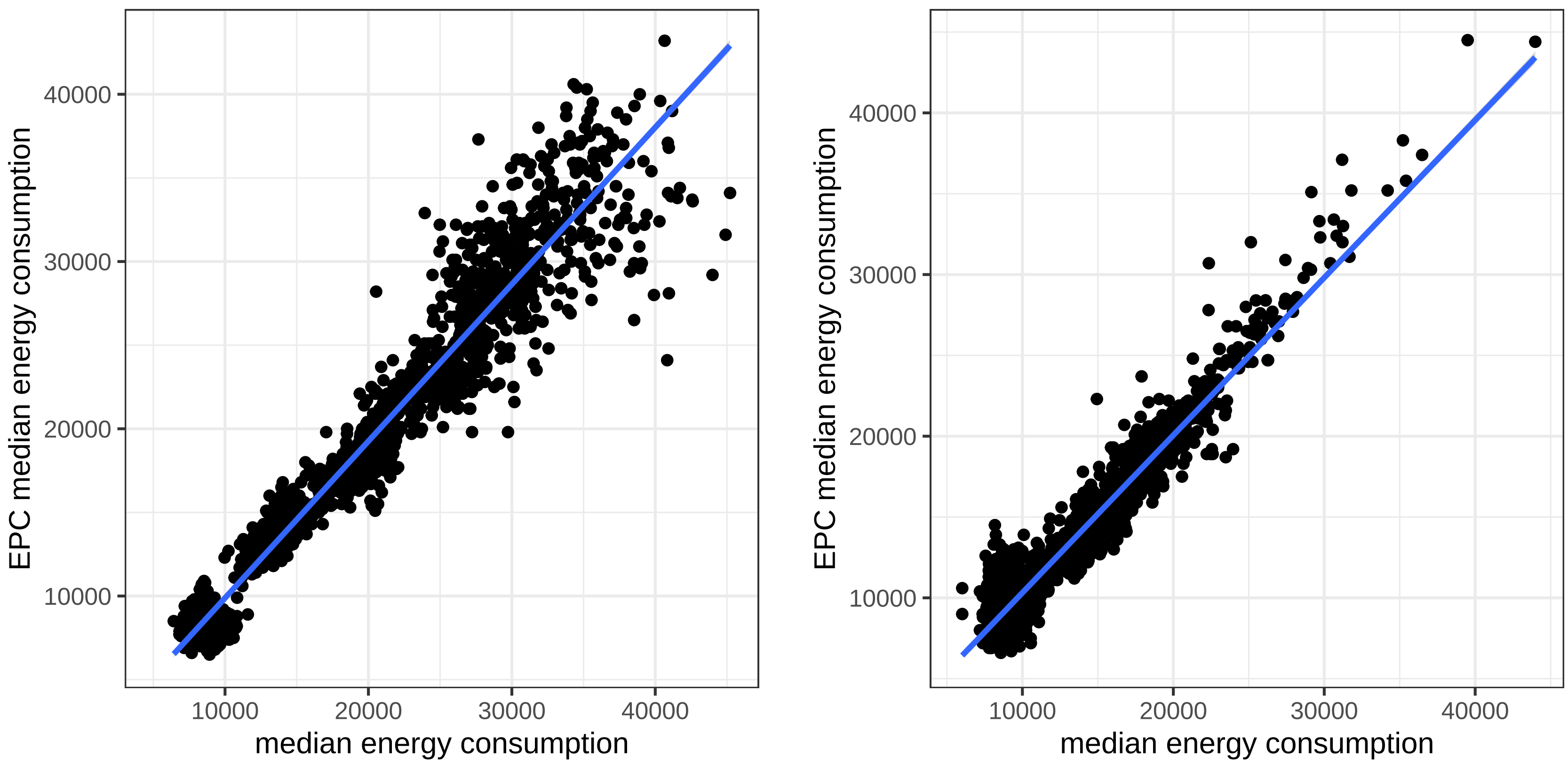


Notes: Figures plot the R^2 that is obtained from validating the derived ensemble consumption measure and three moments: the total, mean, and median consumption against actual consumption data that is published from gas and electricity meters across the country. We compare the goodness-of-fit of each derived moment against the corresponding moment from subnational statistics. The horizontal axis captures the ratio of the number of EPC properties against the population of properties in an area based on council tax data. A value of 0.4 on the axis implies that the estimating sample includes data from all MSOAs that have at most 40% of their building stock captured in the EPC data.

Figure 5: Unconditional raw scatter plot district-by-floor-area or district-by-property-type median energy consumption data vis-a-vis our EPC-derived ensemble consumption estimate

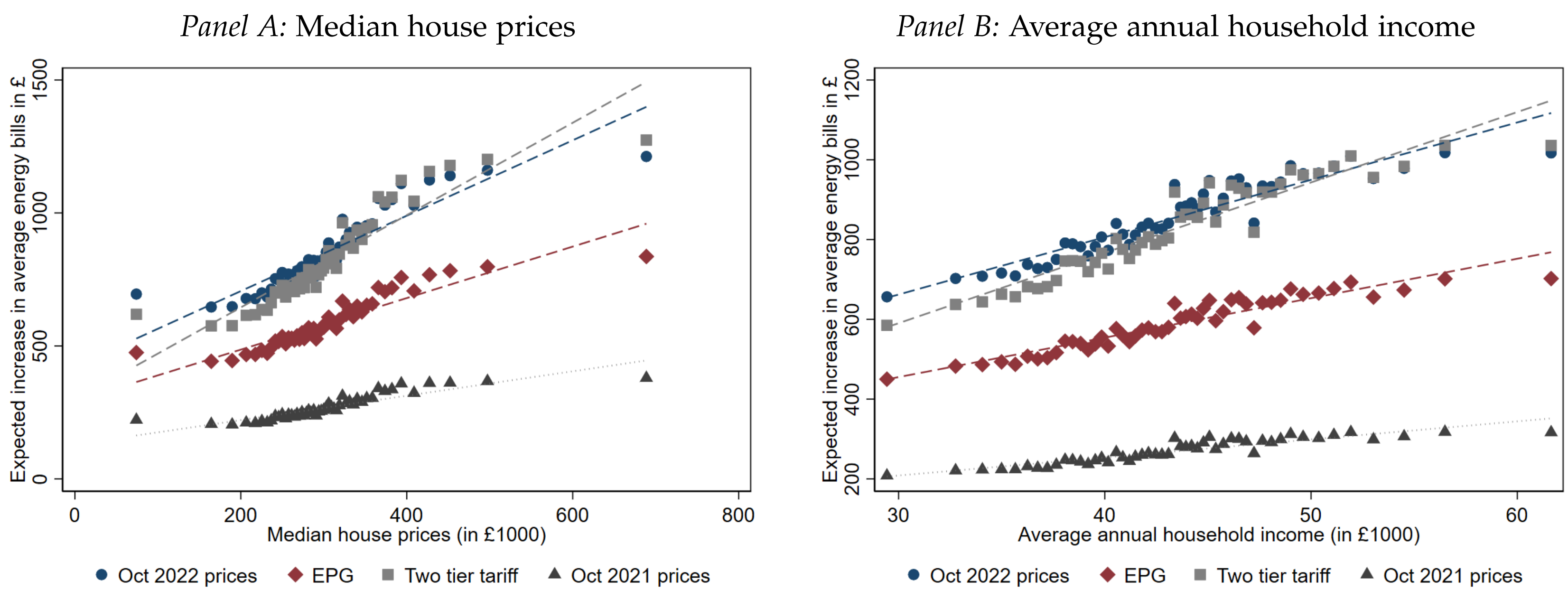
Panel A: District x Floor Area Band

Panel B: District x Property Type



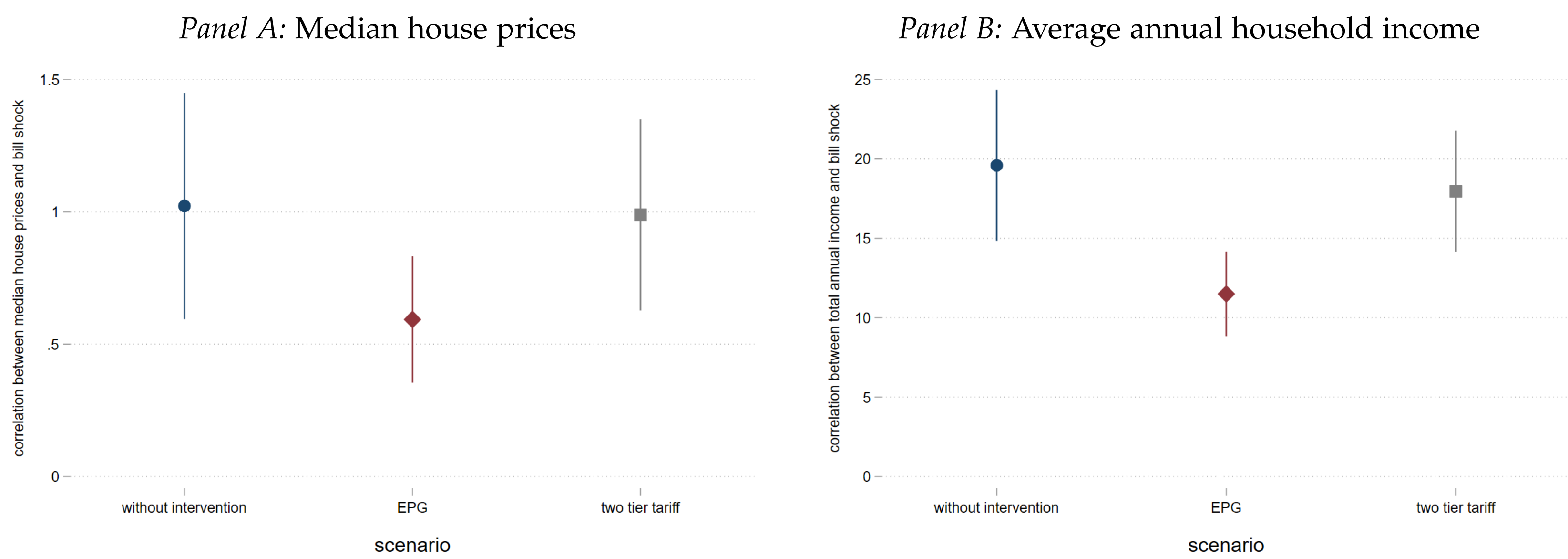
Notes: Figures plot a raw scatterplot of the median district-level energy consumption by floor area in Panel A or district-level energy consumption by property type in Panel B against the corresponding median constructed from our EPC-derived ensemble measure. The corresponding regression is presented in column 10 of Table 1 and Table A1 respectively.

Figure 6: Visualisation of the empirical link between measures of affluence and the expected increase in average energy bills under Ofgem prices (market price proxy), the EPG, and the alternative two-tier tariff



Notes: Figures plot the relationship between median house prices at the MSOA-level against the expected increase in the energy bills to study the degree to which the specific measures are targeted in providing relief.

Figure 7: Comparison of income/wealth gradient in the energy price shock incidence under alternative price policies

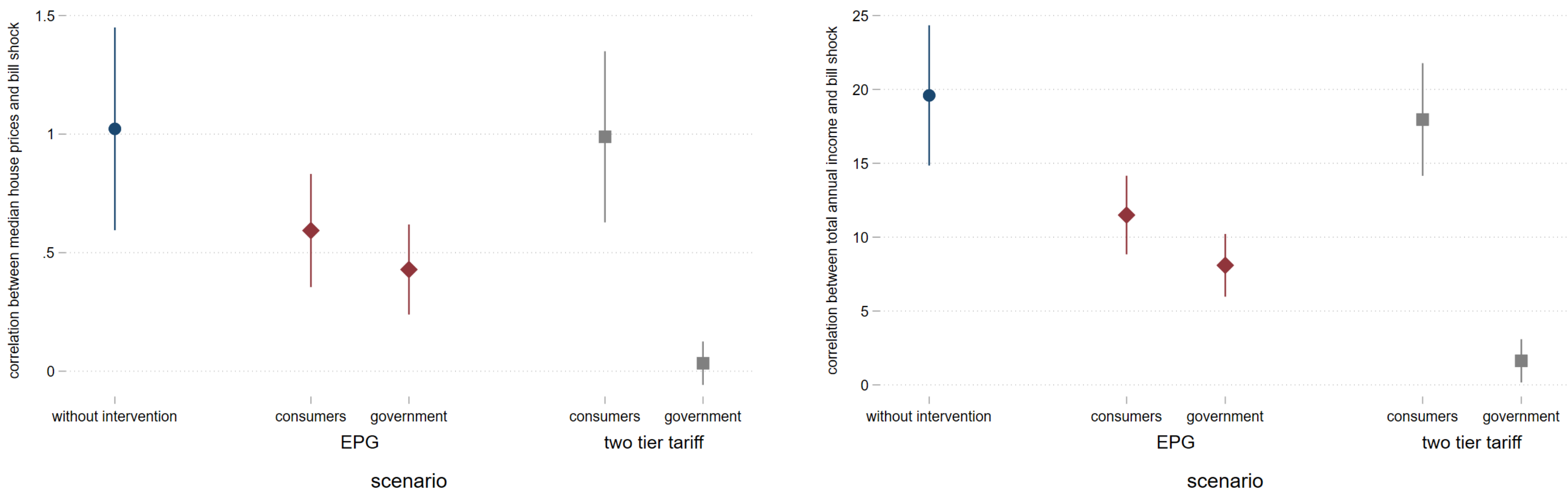


Notes: Figures present regression results showing how the energy-price shock on average bills varies with socio-economic measures at the MSOA-level capturing income or wealth. The "without intervention" scenario shows the overall shock to bills between 2021 and 2022. All regressions include district fixed-effects. Standard errors are clustered at the district level. Bars indicate 95% confidence intervals.

Figure 8: Comparison of income/wealth gradient in the energy price shock incidence under alternative price policies, decomposing consumer- and government-facing shocks

Panel A: Median house prices

Panel B: Average annual household income



Notes: Figures present regression results showing how the energy-price shock on average bills varies with socio-economic measures at the MSOA-level capturing income or wealth. The "without intervention" scenario shows the overall shock to bills between 2021 and 2022. Correlations under EPG and two-tier pricing are decomposed in consumer-facing shock and government subsidy. All regressions include district fixed-effects. Standard errors are clustered at the district level. Bars indicate 95% confidence intervals.

Table 1: Comparison of district-by-floor-area BEIS-reported average and median electricity and gas consumption vis-a-vis corresponding EPC-derived and rescaled proxy measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	EPC		*NEED*		*EPC + Local*		*EPC + NEED + Local*		*Average*	
Panel A: No controls										
Derived energy consumption proxy	0.859***	0.857***	0.924***	0.929***	0.977***	1.067***	1.035***	1.129***	0.919***	0.938***
	(0.011)	(0.011)	(0.015)	(0.014)	(0.007)	(0.005)	(0.010)	(0.009)	(0.010)	(0.009)
R2	0.884	0.899	0.884	0.895	0.957	0.966	0.944	0.950	0.927	0.933
Observations	1650	1650	1650	1650	1650	1650	1650	1650	1650	1650
Panel B: Floor Area Band FE										
Derived energy consumption proxy	0.192***	0.298***	0.185***	0.298***	0.580***	0.806***	0.525***	0.714***	0.357***	0.484***
	(0.029)	(0.031)	(0.039)	(0.041)	(0.039)	(0.037)	(0.047)	(0.044)	(0.042)	(0.042)
R2	0.953	0.947	0.952	0.946	0.971	0.973	0.965	0.964	0.958	0.955
Observations	1650	1650	1650	1650	1650	1650	1650	1650	1650	1650
Panel C: District FE										
Derived energy consumption proxy	0.901***	0.890***	0.960***	0.955***	0.986***	1.071***	1.046***	1.137***	0.939***	0.952***
	(0.009)	(0.009)	(0.012)	(0.012)	(0.007)	(0.006)	(0.009)	(0.008)	(0.008)	(0.008)
R2	0.943	0.949	0.929	0.931	0.972	0.978	0.959	0.963	0.959	0.961
Observations	1650	1650	1650	1650	1650	1650	1650	1650	1650	1650
Panel D: District FE and Floor Area Band FE										
Derived energy consumption proxy	0.196***	0.286***	0.109***	0.185***	0.399***	0.606***	0.278***	0.448***	0.265***	0.367***
	(0.024)	(0.026)	(0.027)	(0.029)	(0.026)	(0.028)	(0.038)	(0.042)	(0.031)	(0.034)
R2	0.986	0.982	0.984	0.979	0.989	0.988	0.986	0.983	0.986	0.983
Observations	1650	1650	1650	1650	1650	1650	1650	1650	1650	1650
Moment:	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median

Notes: Table presents regression results comparing the district-level average electricity and gas consumption average from BEIS micro data by floor-area type with the measures that we constructed as part of our proxy variables. Across the panels more control variables are included. The goodness-of-fit improves and even after controlling for district- and floor-area band, the district specific measures carry strong signal. The observation that the coefficient is near one suggests that the calibration exercise is not producing a biased estimate of the population mean despite the data being from a subsample of the population of properties.

Table 2: Correlates of the exposure to the energy-price shock at the MSOA level - best-subset selection approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
median house price	2.686***	2.201***	1.685***	1.620***	1.446***	1.318***	1.187***	1.108***	1.079***	1.094***	1.069***	1.098***	1.091***	1.089***	1.078***	1.073***
	(0.337)	(0.338)	(0.337)	(0.342)	(0.346)	(0.348)	(0.335)	(0.337)	(0.334)	(0.339)	(0.340)	(0.343)	(0.342)	(0.343)	(0.348)	(0.348)
% population in social rented accommodation		-9.735***				-16.655***	-8.432***	-5.977***	-9.189***	-8.414***	-9.304***	-9.838***	-9.982***	-10.225***	-9.824***	-9.740***
		(0.881)				(1.275)	(1.321)	(1.344)	(1.683)	(1.725)	(2.018)	(2.052)	(2.092)	(2.218)	(2.445)	(2.407)
% population aged 65 plus			40.057***	57.770***	54.323***		30.258***	43.072***	35.037***	33.565***	30.095***	29.723***	31.090***	31.761***	31.624***	31.495***
			(4.916)	(6.409)	(6.138)		(3.906)	(6.429)	(6.883)	(6.781)	(8.526)	(8.481)	(7.950)	(7.790)	(7.741)	(7.869)
% population disabled			-42.397***	-64.503***	-66.713***			-27.670***	-28.534***	-26.044***	-25.232***	-26.965***	-32.036***	-32.773***	-32.904***	-32.873***
			(5.330)	(7.840)	(7.690)			(8.469)	(8.461)	(8.227)	(8.592)	(8.750)	(9.040)	(9.379)	(9.421)	(9.433)
% population in fuel poverty				28.528***	33.629***	54.710***	36.241***	38.844***	48.918***	49.522***	47.993***	47.439***	47.387***	46.945***	45.928***	45.810***
				(5.586)	(5.875)	(6.898)	(5.976)	(6.482)	(7.415)	(7.347)	(7.710)	(7.654)	(7.681)	(8.262)	(8.282)	(8.356)
population density					-3.968***	-4.567***	-4.778***	-4.609***	-4.295***	-4.023***	-4.004***	-4.077***	-4.065***	-4.079***	-4.031***	-4.041***
					(0.815)	(0.801)	(0.756)	(0.741)	(0.735)	(0.695)	(0.699)	(0.703)	(0.705)	(0.700)	(0.709)	(0.702)
% population with university degree						16.265***	16.503***	12.417***	13.467***	14.879***	15.236***	17.137***	17.217***	17.316***	17.632***	17.612***
						(2.972)	(2.849)	(2.865)	(2.911)	(2.973)	(3.017)	(3.360)	(3.380)	(3.374)	(3.526)	(3.527)
% population in private rented accommodation						-16.342***			-7.678***	-6.939***	-8.022***	-8.818***	-8.870***	-8.937***	-8.351**	-8.311**
						(2.308)			(2.495)	(2.539)	(3.047)	(3.104)	(3.128)	(3.149)	(3.301)	(3.276)
% households with more than 2 members							17.564***	15.411***	9.502***	9.435***	8.251***	8.762***	8.800***	8.740***	8.076**	8.061**
							(2.618)	(2.686)	(3.054)	(3.054)	(3.121)	(3.112)	(3.115)	(3.130)	(3.335)	(3.345)
% population commuting with public transport										-6.758*	-6.719*	-6.538*	-6.676*	-6.919**	-6.867**	-6.875**
										(3.465)	(3.492)	(3.474)	(3.426)	(3.428)	(3.404)	(3.404)
% inactive											4.213	3.513	3.295	3.476	3.724	3.679
											(3.779)	(3.869)	(3.728)	(3.876)	(3.857)	(3.829)
average annual household income												-4.901	-4.979	-4.888	-5.139	-5.119
												(3.679)	(3.666)	(3.654)	(3.730)	(3.740)
% population in bad or very bad health													11.193	10.001	9.646	9.544
													(17.024)	(16.086)	(16.120)	(16.054)
% unemployed														6.269	6.986	6.813
														(14.300)	(14.310)	(14.274)
% population in whole house or bungalow															0.894	0.871
															(1.547)	(1.553)
% population in shared accommodation																-5.304
																(14.218)
Best Subset												X				
Observations	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789
R2	.346	.359	.37	.381	.388	.394	.398	.4	.401	.402	.403	.403	.403	.403	.403	.403

Notes: Table presents best-subset-selection regression results. The best-subset is indicated in the table footer. All regressions control for district fixed effects. The analysis presents correlational patterns that help characterize the incidence of the energy price shock in terms of the socio-economic characteristics of areas that are expected to be hit the most. Standard errors are clustered at the district level.

Table 3: Correlates of the energy-savings potential at the MSOA level - best-subset selection approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
median house price	1.244***	0.900***	0.999***	0.856***	0.671***	0.612***	0.548***	0.505***	0.513***	0.543***	0.526***	0.511***	0.510***	0.499***	0.494***	0.495***
	(0.151)	(0.146)	(0.170)	(0.160)	(0.159)	(0.154)	(0.157)	(0.159)	(0.161)	(0.164)	(0.163)	(0.161)	(0.162)	(0.163)	(0.165)	(0.166)
% population in social rented accommodation		-6.900***	-10.524***	-10.556***	-12.631***	-11.664***	-11.809***	-10.487***	-10.040***	-10.901***	-10.615***	-9.972***	-10.316***	-9.847***	-9.933***	-9.908***
		(0.431)	(0.668)	(0.643)	(0.737)	(0.700)	(0.703)	(0.795)	(0.831)	(0.903)	(0.897)	(1.001)	(1.040)	(1.228)	(1.412)	(1.436)
% population in fuel poverty			19.510***	24.122***	35.739***	35.275***	36.745***	37.355***	37.669***	37.007***	36.381***	34.478***	33.909***	32.921***	32.667***	32.646***
			(2.891)	(2.874)	(3.959)	(3.733)	(3.854)	(4.003)	(3.972)	(3.956)	(4.072)	(4.491)	(4.785)	(4.662)	(5.132)	(5.097)
% population aged 65 plus				13.496***		9.336***	8.262***	14.512***	13.707***	12.418***	12.101***	13.719***	15.099***	15.180***	14.783***	14.529***
				(1.695)		(1.676)	(1.599)	(3.724)	(3.596)	(3.632)	(3.718)	(3.784)	(3.564)	(3.607)	(4.540)	(4.279)
% population with university degree					6.936***	6.667***	6.786***	5.208***	6.011***	8.141***	8.147***	8.866***	9.032***	9.377***	9.385***	9.376***
					(1.389)	(1.313)	(1.349)	(1.306)	(1.338)	(1.557)	(1.556)	(1.580)	(1.586)	(1.652)	(1.652)	(1.661)
% population in private rented accommodation					-9.324***	-6.909***	-6.338***	-5.944***	-5.509***	-6.785***	-6.578***	-5.315***	-5.379***	-4.705***	-4.785**	-4.771**
					(1.127)	(1.071)	(1.090)	(1.104)	(1.169)	(1.288)	(1.269)	(1.484)	(1.490)	(1.688)	(1.869)	(1.883)
population density							-1.364***	-1.306***	-1.154***	-1.224***	-1.256***	-1.320***	-1.340***	-1.290***	-1.282***	-1.285***
							(0.368)	(0.356)	(0.329)	(0.330)	(0.327)	(0.318)	(0.314)	(0.311)	(0.318)	(0.320)
% population disabled								-11.828**	-10.407**	-12.390***	-12.464***	-11.186**	-13.115***	-13.464***	-13.376***	-12.370**
								(4.817)	(4.611)	(4.563)	(4.574)	(4.680)	(4.359)	(4.509)	(4.682)	(4.920)
% population commuting with public transport									-3.805**	-3.597**	-3.640**	-3.598**	-3.973**	-3.914**	-3.923**	-3.905**
									(1.736)	(1.739)	(1.738)	(1.733)	(1.674)	(1.649)	(1.639)	(1.620)
average annual household income										-5.514***	-5.455***	-5.846***	-5.793***	-6.141***	-5.991***	-5.974***
										(1.882)	(1.878)	(1.831)	(1.811)	(1.871)	(1.950)	(1.943)
% population in shared accommodation											-16.695**	-15.923**	-15.520**	-15.221**	-15.071**	-15.114**
											(7.349)	(7.240)	(7.121)	(7.197)	(6.905)	(6.836)
% households with more than 2 members												2.701	2.692	2.062	1.853	1.834
												(1.671)	(1.665)	(1.842)	(1.828)	(1.843)
% unemployed													9.159	9.766	10.085	10.365
													(7.977)	(7.909)	(8.621)	(8.252)
% population in whole house or bungalow														0.956	1.011	1.021
														(0.921)	(0.855)	(0.863)
% inactive															0.583	0.638
															(2.400)	(2.307)
% population in bad or very bad health																-2.351
																(9.121)
Best Subset													X			
Observations	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789	6789
R2	.314	.34	.36	.374	.379	.384	.387	.389	.39	.391	.391	.392	.392	.392	.392	.392

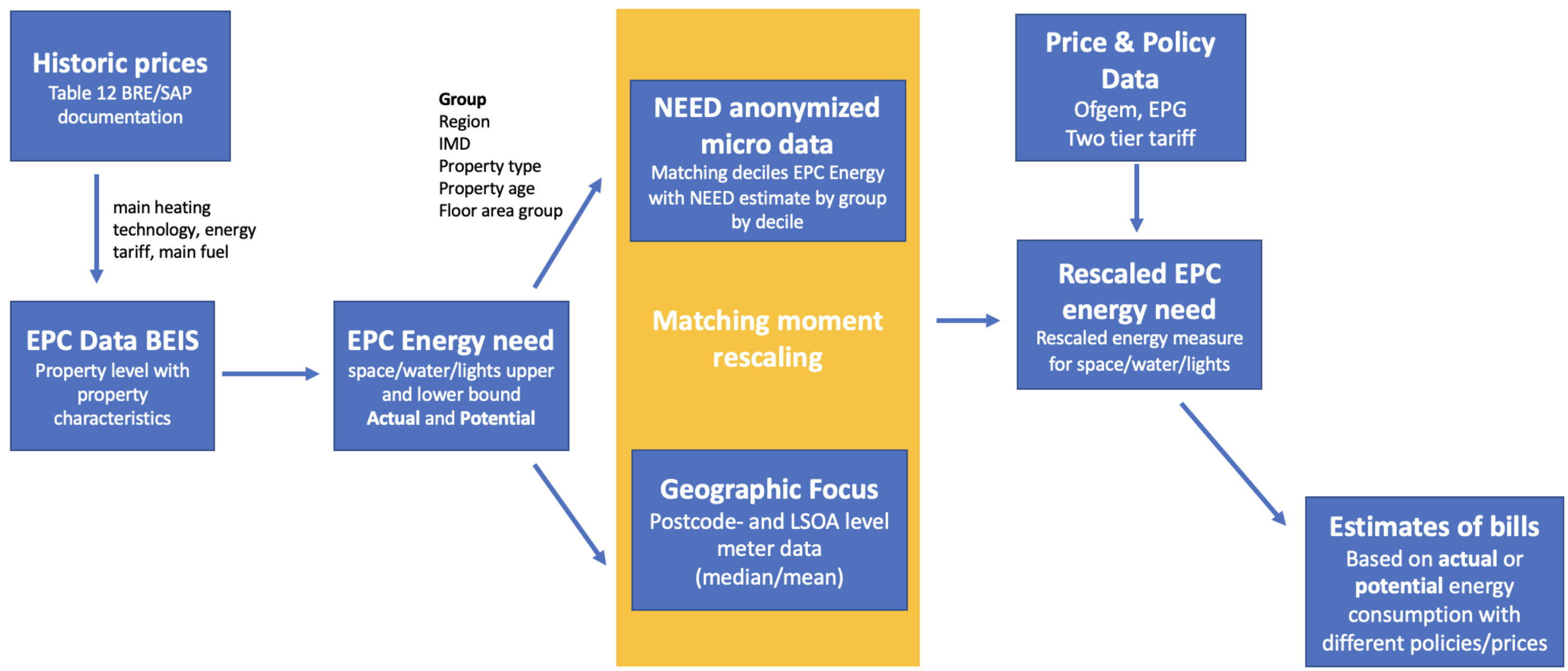
Notes: Table presents best-subset-selection regression results. The best-subset is indicated in the table footer. All regressions control for district fixed effects. The analysis presents correlational patterns that help characterize the variation in energy savings potential in terms of the socio-economic characteristics of areas. Standard errors are clustered at the district level.

Table 4: Comparison of income-wealth gradient in the value of the energy-savings potential contrasting the full price shock, the EPG-mitigated, and the two-tier tariff mitigated shock

	(1)	(2)	(3)
Energy savings incentive	*without intervention*	*with EPG*	*with two tier tariff*
Panel A:			
median house price	1.244***	0.853***	1.526***
	(0.151)	(0.103)	(0.178)
R2	0.281	0.288	0.302
Observations	6789	6789	6789
Panel B:			
average annual household income	15.029***	10.349***	18.436***
	(0.968)	(0.670)	(1.110)
R2	0.245	0.250	0.258
Observations	6789	6789	6789
Panel C:			
income rank	0.070***	0.048***	0.085***
	(0.004)	(0.003)	(0.005)
R2	0.264	0.270	0.279
Observations	6789	6789	6789
District FE:	X	X	X

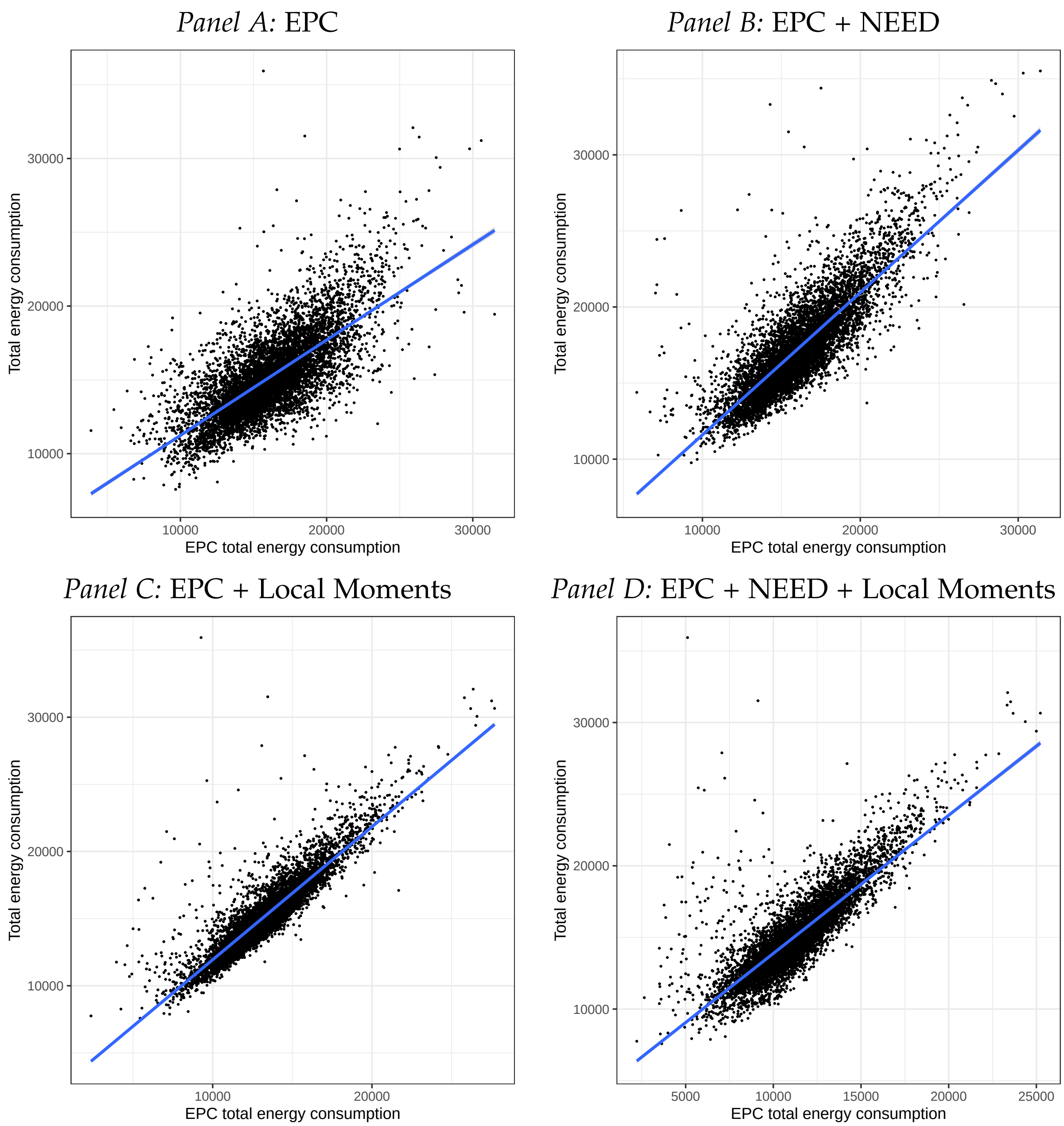
Notes: Table presents regression results showing how the various energy-price shock measures affect the gradient of average energy savings potential with respect to various socio-economic measures at the MSOA-level capturing income or wealth. Column 1 displays the overall shock to bills between 2021 and 2022. Column 2 presents the energy savings potential under the EPG, while column 3 presents it under the two-tier tariff. All regressions include district fixed-effects. Standard errors are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Figure A1: Schematic flowchart of the data processing pipeline to arrive at household-level energy price shock exposure measure



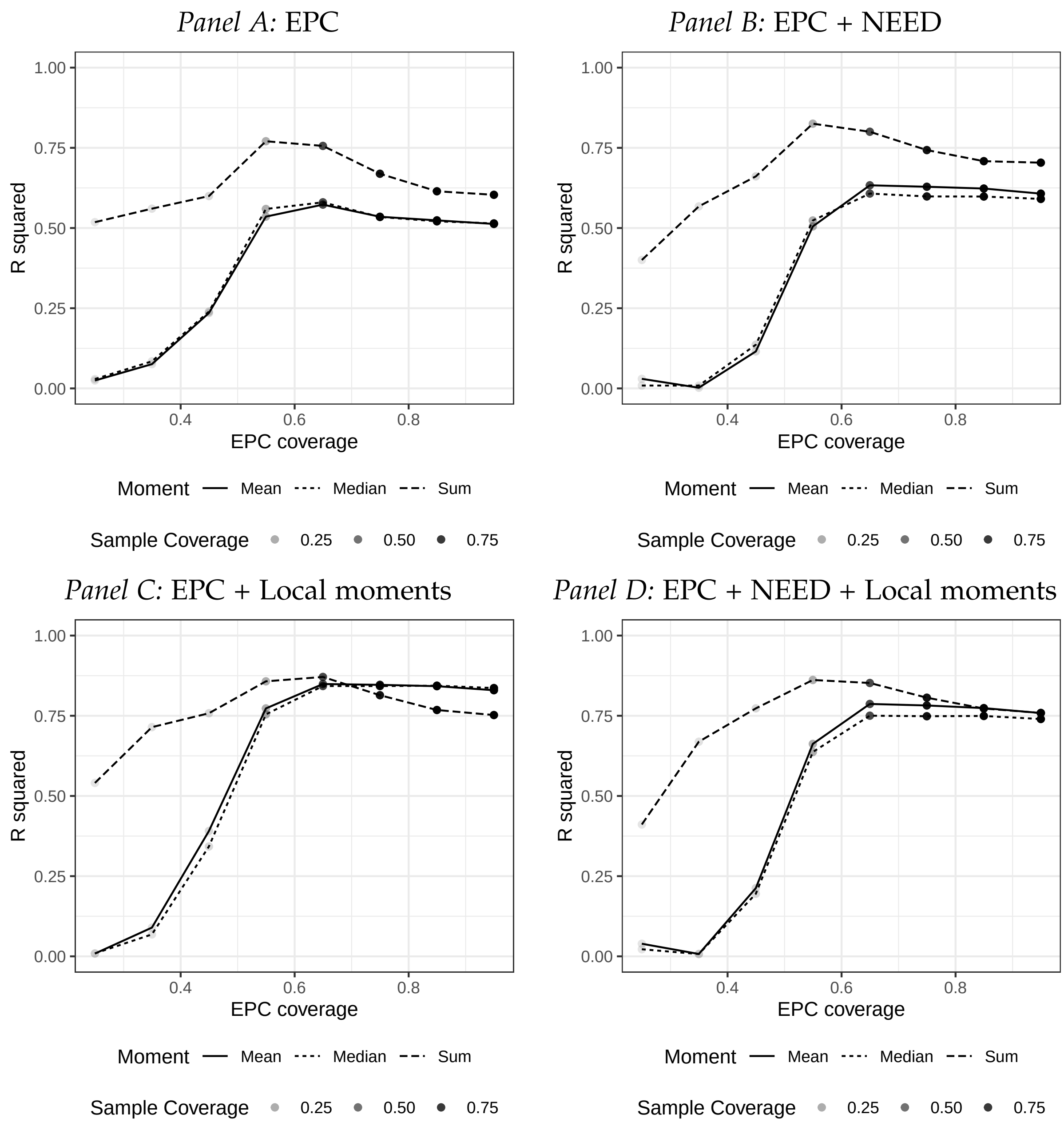
Notes: Figure provides a visual summary of the data construction process and the different steps and inputs that go into the derivation of the energy consumption and bill estimates.

Figure A2: Median property-level energy consumption measures at the MSOA-level compared with median imputed energy consumption measures from EPC-NEED data



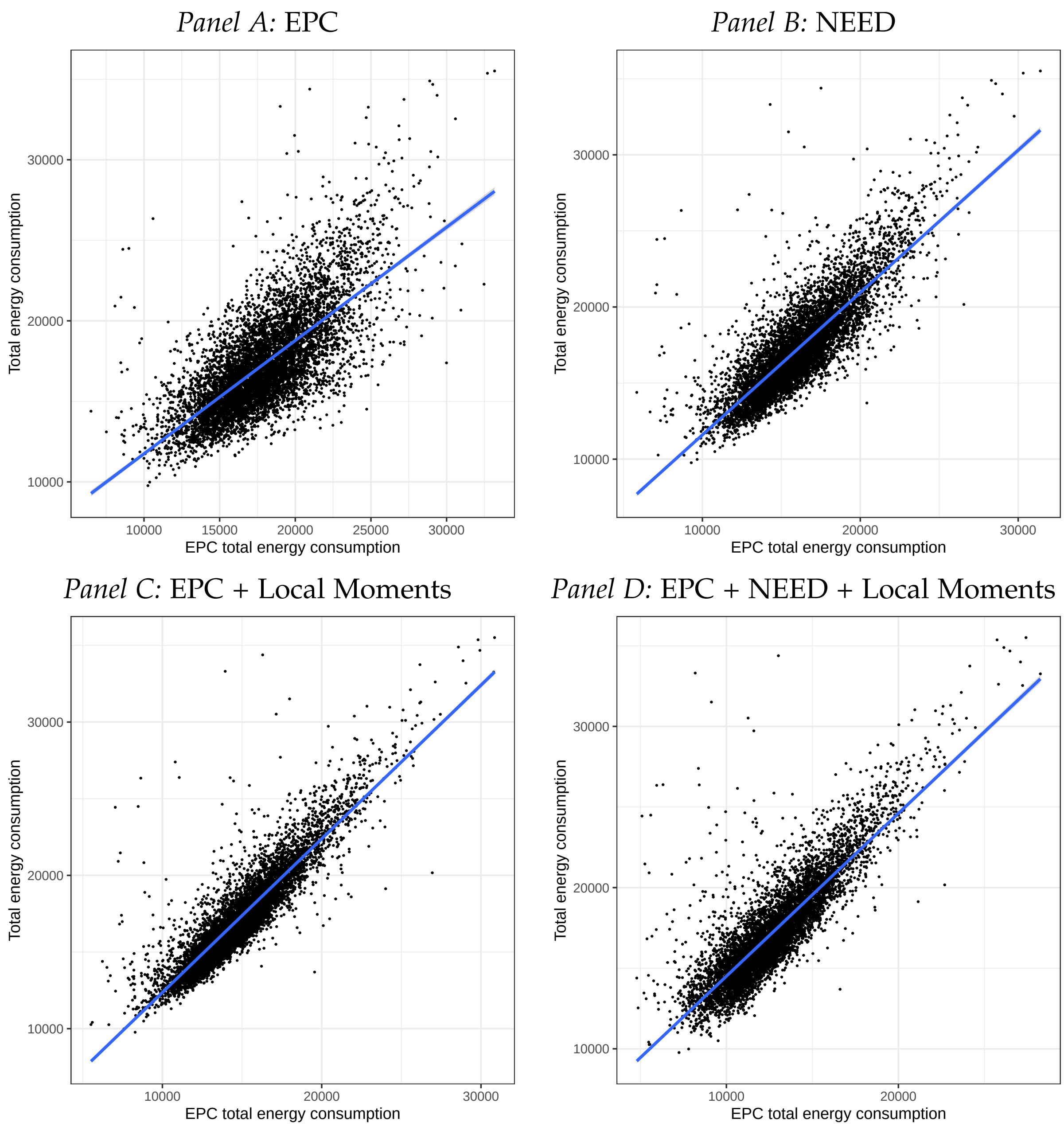
Notes: Figures provide a scatterplot of estimates of the median energy consumption per meter from published data at the MSOA-level (for metered electricity and gas only) on the vertical axis and the median of various imputed energy consumption measures that leverage different data on the horizontal axis. Panel A provides the implied consumption estimates from the EPC data as is. Panel B augments the EPC data with a matching-of-moments approach based on anonymized individual level meter reading data collected under the NEED framework. Panel C uses the EPC raw energy consumption estimates and augments it with matched granular area-specific moments. Panel D is the final measure that combines the EPC raw data, the property-specific moment-matching and the local area specific moment matching.

Figure A3: Correlation between moments of derived consumption proxy measures and moments from actual consumption data



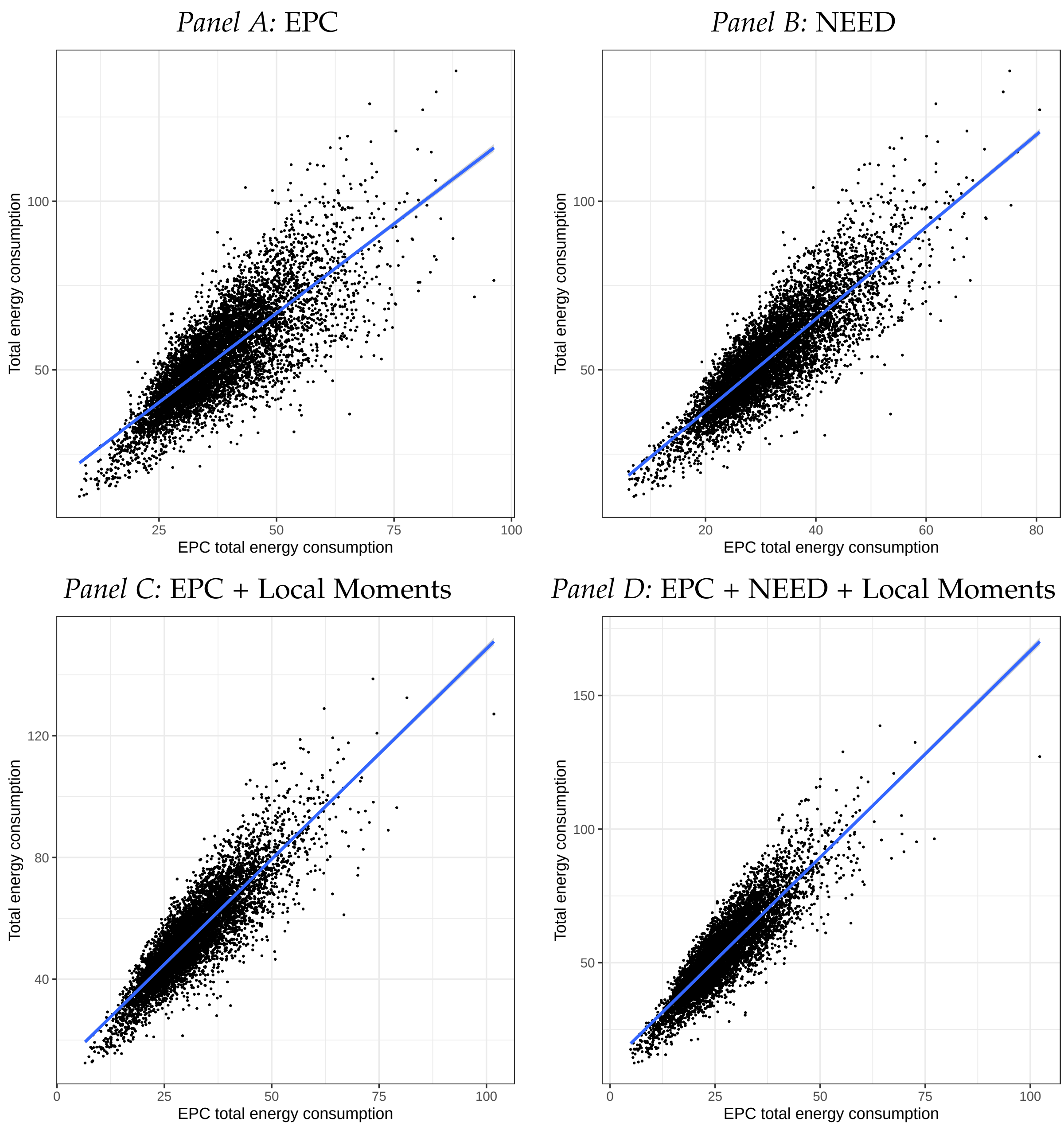
Notes: Figures plot the R^2 that is obtained from validating the derived implied consumption measures and three moments: the total consumption, the mean, and median consumption against actual consumption data that is published from gas and electricity meters across the country. For the four different derived measures, we compare the goodness-of-fit of the three moments against the corresponding moment from subnational statistics. The horizontal axis captures the ratio of the number of EPC properties against the population of properties in an area based on council tax data. A value of 0.4 on the axis implies that the estimating sample includes data from all MSOAs that have at most 40% of their building stock captured in the EPC data. We note that the goodness-of-fit remains stable across each of the moments when the estimating sample includes MSOAs with an EPC coverage of up to 60%.

Figure A4: Average property-level energy consumption measures at the MSOA-level compared with imputed energy consumption measures from EPC-NEED data



Notes: Figures provide a scatterplot of the mean energy consumption per meter estimates from published data at the MSOA level (for metered electricity and gas only) on the vertical axis and the average of various imputed energy consumption measures that leverage different data on the horizontal axis. Panel A provides the implied consumption estimates from the EPC data as is. Panel B augments the EPC data with a matching-of-moments approach based on anonymized individual level meter reading data collected under the NEED framework. Panel C uses the EPC raw energy consumption estimates and augments it with matched granular area-specific moments. Panel D is the final measure that combines the EPC raw data, the property-specific moment-matching and the local area specific moment matching.

Figure A5: Total property-level energy consumption measures at the MSOA-level compared with imputed energy consumption measures from EPC-NEED data



Notes: Figures provide a scatterplot of the total energy consumption per meter estimates from published data at the MSOA level (for metered electricity and gas only) on the vertical axis and the average of various imputed energy consumption measures that leverage different data on the horizontal axis. Panel A provides the implied consumption estimates from the EPC data as is. Panel B augments the EPC data with a matching-of-moments approach based on anonymized individual level meter reading data collected under the NEED framework. Panel C uses the EPC raw energy consumption estimates and augments it with matched granular area-specific moments. Panel D is the final measure that combines the EPC raw data, the property-specific moment-matching and the local area specific moment matching.

Table A1: Comparison of district-by-property-type BEIS-reported average and median electricity and gas consumption vis-a-vis corresponding EPC-derived and rescaled proxy measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	EPC		*NEED*		*EPC + Local*		*EPC + NEED + Local*		*Average*	
Panel A: No controls										
Derived energy consumption proxy	0.789***	0.859***	0.903***	0.975***	0.949***	1.071***	0.993***	1.121***	0.888***	0.975***
	(0.013)	(0.011)	(0.013)	(0.010)	(0.008)	(0.011)	(0.010)	(0.012)	(0.010)	(0.009)
R2	0.756	0.850	0.823	0.896	0.887	0.942	0.881	0.927	0.845	0.918
Observations	2303	2303	2303	2303	2303	2303	2303	2303	2303	2303
Panel B: Property Type FE										
Derived energy consumption proxy	0.697***	0.782***	0.810***	0.892***	0.989***	1.111***	0.969***	1.102***	0.891***	0.968***
	(0.038)	(0.037)	(0.032)	(0.029)	(0.017)	(0.028)	(0.022)	(0.032)	(0.024)	(0.024)
R2	0.822	0.888	0.846	0.906	0.899	0.947	0.882	0.928	0.871	0.929
Observations	2303	2303	2303	2303	2303	2303	2303	2303	2303	2303
Panel C: District FE										
Derived energy consumption proxy	0.807***	0.863***	0.930***	0.994***	0.937***	1.057***	1.004***	1.130***	0.888***	0.969***
	(0.009)	(0.008)	(0.011)	(0.010)	(0.007)	(0.009)	(0.010)	(0.011)	(0.008)	(0.008)
R2	0.807	0.891	0.853	0.920	0.888	0.947	0.881	0.932	0.863	0.933
Observations	2303	2303	2303	2303	2303	2303	2303	2303	2303	2303
Panel D: District FE and Property Type FE										
Derived energy consumption proxy	0.707***	0.729***	0.855***	0.893***	0.951***	1.056***	1.020***	1.150***	0.893***	0.922***
	(0.033)	(0.039)	(0.043)	(0.047)	(0.024)	(0.038)	(0.040)	(0.053)	(0.027)	(0.035)
R2	0.883	0.936	0.876	0.931	0.902	0.952	0.883	0.933	0.894	0.947
Observations	2303	2303	2303	2303	2303	2303	2303	2303	2303	2303
Moment:	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median

Notes: Table presents regression results comparing the district-level average electricity and gas consumption average from BEIS micro data by property type (detached, semi-detached, (mid/end) terraced, flat and/or bungalow) with the measures that we constructed as part of our proxy variables.

Table A2: Comparison of income/wealth gradient in the energy price shock incidence under alternative price policies

	(1)	(2)	(3)	(4)	(5)
Energy bill shock	*without intervention*	*with EPG*		*with two tier tariff*	
		Consumers	Govt	Consumers	Govt
Panel A:					
median house price	2.686***	1.492***	1.194***	2.852***	-0.166***
	(0.337)	(0.186)	(0.152)	(0.321)	(0.058)
R2	0.315	0.324	0.301	0.394	0.188
Observations	6789	6789	6789	6789	6789
Panel B:					
average annual household income	34.175***	19.131***	15.044***	35.936***	-1.761**
	(2.176)	(1.253)	(0.933)	(1.793)	(0.749)
R2	0.276	0.284	0.266	0.326	0.186
Observations	6789	6789	6789	6789	6789
Panel C:					
Income Rank (IMD)	0.154***	0.085***	0.069***	0.156***	-0.003
	(0.009)	(0.005)	(0.004)	(0.007)	(0.003)
R2	0.296	0.304	0.286	0.350	0.185
Observations	6789	6789	6789	6789	6789
District FE:	X	X	X	X	X

Notes: Table presents regression results showing how various energy-price shock measures on average bills vary with various socio-economic measures at the MSOA-level capturing income or wealth. Column 1 displays the overall shock to bills between 2021 and 2022. Columns 2 and 3 decompose this shock in the consumer- and the government-facing average bill increase under the EPG. Columns 4 and 5 present the same breakdown for the two-tier tariff intervention. All regressions include district fixed-effects. Standard errors are clustered at the district level with stars indicating *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Appendix to "Distributional and climate implications of policy responses to the energy crisis: Lessons from the UK"

For Online Publication

Thiemo Fetzer Ludovica Gazze Menna Bishop

A Step 1: Deriving a physical energy consumption measure for each property in the EPC data

An essential ingredient in our energy consumption calculations was the set of fuel prices faced by a given property for each type of energy consumption (space heating, water heating, and lighting). For example, while gas is the most common heating method across properties in the EPC data, many use either electricity or oil and therefore face different prices. Additional complexity follows from the range of possible tariffs used to price a household's electricity use. The prices used in EPC calculations dating back to 2013 for all possible fuel types are published by BRE.[1] We had to infer which of these had been applied to each energy consumption type for each property in order to estimate expenditures.

To decide the assignment of fuel prices, we consulted four variables from the EPC database: main heating system (`MAINHEAT_DESCRIPTION`), water heating system (`HOTWATER_DESCRIPTION`), type of fuel used to power the central heating (`MAIN_FUEL`), and electricity tariff (`ENERGY_TARIFF`). For example, if the main heating system was recorded as "boiler and radiators, mains gas", main fuel as "mains gas", hot water system as "from main system" and energy tariff as "single", a property was assigned the "mains gas" fuel price for space and water heating and the "standard tariff" price for lighting from the SAP price list. The raw data contain 9,796 unique combinations of these four variables, and so we restricted our attention to the 30 most common combinations, excluding those containing oil.[2] In total, these 30 com-

[1] Data are available here https://bregroup.com/sap/standard-assessment-procedure-sap-2012/

[2] We excluded properties using oil as there is no price cap for this fuel, which is our source of price data for gas and electricity (see the next section for details).

binations account for 85% of the sample. For the remaining 15%, we infer energy consumption using ENERGY_CONSUMPTION_CURRENT, a variable which estimates total energy consumption in kWh per metre squared of floor area. We scale this variable by FLOOR_AREA and multiply by the cost share of each energy use type to produce estimates of energy consumption for space and water heating and lighting.

We followed the SAP documentation to the best of our ability in the process of assigning fuel prices to energy consumption types, though in places the appropriate correspondence was not clear. Ambiguities also arose in interpreting how prices, which include a standing charge and price per kWh, had been applied to consumption to produce the spending estimates available in EPC data, complicating the reverse-engineering of this calculation. To account for this uncertainty, we have included a lower-bound estimate, which incorporates standing charges, as well as an upper-bound estimate, which excludes standing charges from consumption calculations. This inevitably introduces some measurement error, which we intended to tackle via spatial aggregation.

The consumption estimates we produce for water heating, space heating and lighting are *intention-to-treat* estimates, as the underlying physical SAP model used to produce the EPC data considers three factors:

1. The physical characteristics of a property, such as build-type, insulation technology, floor area, window area, number of rooms and light fixtures
2. Time-invariant climatic factors that affect fuel demand and are ultimately determined by property location
3. Fixed relationships between estimated use due to time-invariant estimates of likely occupation and use determined by the physical makeup of the property such as the number of bedrooms, the floor area, etc.

Consumption estimates stemming from EPC data will therefore not map one-to-one with consumption estimates which reflect actual patterns of energy consumption by residents, such as those produced from meter readings. Rather, EPC data is based on exogenous and typically fixed characteristics of the underlying buildings, a desirable feature for an econometrician. In this sense, our consumption estimates should be understood as *theoretical* as opposed to *real* consumption estimates.

B Step 2: Anchoring technically-required energy consumption measure with anonymized meter-level data

In step two, we produce a second consumption measure that incorporates anonymous micro data on energy and gas consumption from the National Energy Efficiency Data-Framework (NEED).[3] We refer to these as *real* consumption estimates as, unlike the EPC-based estimates, they reflect patterns of energy consumption behaviour by households. The sample includes four million properties and is designed to be representative of domestic properties in England and Wales. Data are available annually for years 2005-19, of which our analysis uses 2017-19. The data include estimates of energy and gas consumption which are derived from meter readings, alongside a number of property and area-level characteristics.

We use this *real* consumption data to develop a refinement of the *theoretical* consumption measure derived in Step 1. We match moments of the NEED meter-level data with moments from the EPC-derived consumption measure, in effect rescaling our theoretical consumption measure. This is possible because the NEED data include a range of property characteristics which are also present in the EPC data:

- property type (six categories)
- property age band (four categories)
- an indicator for whether gas is the main heating fuel (two categories)
- floor area band (five categories)
- a measure of the relative deprivation of the area in which a property is located, measured in 2019 (five categories each for Wales and England)
- region (nine categories for England, one for Wales).

In theory, there are $6 \times 4 \times 2 \times 5 \times 5 \times 9 = 10,800$ unique combinations of these features in England and $6 \times 4 \times 2 \times 5 \times 5 = 1,200$ unique combinations in Wales.

For each unique combination, we calculate the deciles of combined gas and electricity consumption in the NEED data, excluding combinations which contain

[3] The data can be found here `https://www.gov.uk/government/statistics/national-energy-efficiency-data-framework-need-anonymised-data-2021`.

300 properties or fewer out of the total 12 million (4 million for each of the years 2017-19).

We then replicate this exercise using the EPC consumption estimates derived in Step 1. When calculating total consumption, we take weighted averages of the upper and lower bounds for our light, water, and space energy consumption estimates, before summing over these to derive aggregate energy consumption. The weight assigned to the upper bound of each consumption estimate is 5 minus the floor area band (1-5), meaning a higher weight is assigned to the lower bound for larger properties.

Next, we match the NEED energy consumption deciles for each unique combination of property attributes to the corresponding EPC energy consumption deciles. For example, a property that is in the top decile of *theoretical consumption* (derived from EPC data) among properties with the same combination of property attributes will be assigned the top decile of *real consumption* (derived from NEED data) for properties with these same attributes. The latter provides us with a potentially more accurate representation of real consumption behaviour at the property level.

We then update our property-level estimates of theoretical consumption by multiplying by the ratio of real to theoretical energy consumption (both actual and potential) for a property's attributes and consumption decile.[4]

We then perform a second rescaling using postcode-level gas and electricity consumption data, again for the years 2017-19.[5] For each postcode, we compute the sum of median gas and electricity consumption across years. We then repeat this exercise for the theoretical consumption estimates developed in Step 1 as well as the estimates which were adjusted using NEED data. Next, we rescale the property-level theoretical and NEED-adjusted consumption estimates by multiplying by the ratio of the median postcode-level energy consumption from the postcode data to the corresponding value in the EPC data. We perform this rescaling of theoretical consumption estimates only for properties in postcodes with at least 25% coverage in the EPC data. Here, coverage is defined as the number of properties per postcode

[4]Note that energy consumption estimates for properties whose combinations of attributes included less than 300 properties were not rescaled.

[5]The electricity data can be found on `https://www.gov.uk/government/collections/sub-national-electricity-consumption-data`; the gas data is on `https://www.gov.uk/government/collections/sub-national-gas-consumption-data`.

in the EPC data relative to the number of energy meters used to form the energy consumption estimates in the postcode data.[6] We then perform this same rescaling for NEED-adjusted consumption estimates. We exclude from both rescaling exercises properties in postcodes with five or fewer properties in the EPC data or five of fewer energy meters in the postcode consumption estimates. For properties in postcodes which fail these coverage requirements, we rescale consumption using the same methods but with LSOA-level data. Here, we impose a looser restriction of 50% coverage of EPC properties in a property's LSOA.

C Step 3: Converting consumption measures to time-varying spending estimates

In our third step, we convert the *time-invariant* consumption estimates from Steps 1 and 2, measured in kWh, into *time-varying* estimates of actual spending in GBP. In practice, this is not straightforward as the energy prices faced by households, which consist of a unit price and standing charge, depend on the particular energy supply contract which they have entered into.

We are interested in four types of price scenario:

1. Energy price cap.
   The energy cap sets the maximum price that energy suppliers are allowed to charge customers, and is chosen by regulator Ofgem for gas and electricity prices to reflect the costs of supplying energy and to allow modest profits (Ofgem, 2022a). The cap has been updated every 6 months since its introduction in January 2019, but from October 2022 will be updated on a quarterly basis. The price cap was originally conceived to protect inattentive consumers from being charged unfair rates. In its early years, some energy contracts on the market were cheaper than the cap, but since the summer of 2021 the cap has been the cheapest rate available. This phenomenon is due to price increases between the time at which the price cap is set and the time at which it comes into effect (as of October 2022, this gap has been shortened from two

[6] The postcode-level data includes the number of meters used to form the estimates of median gas and electricity consumption respectively, and we use the highest of these two figures.

months to 25 working days) (Ofgem, 2022b). As such, the cap has been a more accurate reflection of the prices faced by households in recent months than in previous years. Our study incorporates price cap values from October 2021 and October 2022.

2. Energy Price Guarantee.
   In September 2022, the UK government announced the Energy Price Guarantee programme as a response to the ongoing energy crisis. The EPG reduces the maximum per unit rate below the level of the October 2022 price cap in an attempt to limit the average household energy bill to around £2,500. As discussed in Fetzer (2022), the standing charge is maintained at the level of the October 2022 price cap.

3. Historical average energy prices.
   The Department for Business, Energy and Industrial Strategy (BEIS) publishes data on average gas and electricity prices for 2010-2021.[7] These data are particularly valuable for estimating energy bills pre-2019, when the energy price cap had not yet been introduced.

4. Two-tier tariff.
   This is an alternative policy proposal to the energy-price guarantee that is discussed in more detail in Fetzer (2022). It consists of a two-tier tariff wherein the standing charge would be fixed at the level of the October 2021 price cap, as would unit prices for the first 9,500 kWh of natural gas consumption and the first 2,500 kWh of electricity consumption. As 50% of UK households consume less than 12,100 kWh of natural gas and 2,900 kWh of electricity, this would drastically limit energy price increases for the bulk of households.[8] The second tier of the energy tariff would be set at steeper levels which could be aligned with the EPG. For example, a second tier unit price of 20 pence per kWh for natural gas and 60 pence per kWh for electricity, together with the first tier described above, would have a similar cost to the government as the

[7] Data are available here https://www.gov.uk/government/statistical-data-sets/annual-domestic-energy-price-statistics

[8] See https://www.gov.uk/government/statistics/national-energy-efficiency-data-framework-need-consumption-data-tables-2021.

EPG. This would offer much more targeted support without undermining the incentive to save energy created by higher unit prices.

Energy prices consist of a standing charge and unit rate which differ according to region, payment method (for example, direct debit versus pre-paid), fuel type (electricity versus gas), and electricity metering arrangement (whether the electricity tariff varies by time of use). We use information on these dimensions from the EPC data to assign the appropriate price to each property. In the absence of data on payment method, we assume direct debit for all households.[9]

We then estimate energy expenditure for a given property and energy use (space heating, water heating, or lighting) as follows:

$$spend_{ierfmt} = cons_{ierfm} \times price_{rfmt} + charge_{rfmt}$$

Here, $cons_{ierfm}$ is the consumption estimate for energy use type e by property i in region r with fuel f and metering arrangement m, as calculateds in Steps 1 and 2. $price_{rfmt}$ and $charge_{rfmt}$ are the unit price and standing charge at which the cap has been set for their region, metering arrangement and fuel in period t (assuming payment by direct debit).

In essence, this spending calculation converts the intention-to-treat consumption estimate in physical energy units, which reflects the physical characteristics of a property, back into energy cost estimates that are, in turn, exogenous to household-specific choices with respect to their energy supply contract. This data structure is also ideal for merging in different price scenarios to forecast their likely impact on household bills across different groups and regions within the UK.

Most households are on one-year fixed term contracts at the energy supply contracts.

[9]Direct debit is the most popular payment method (Ofgem, 2019).

D Step 4: Energy efficiency upgrade recommendations and its costing

Lastly, we also examine the specific energy efficiency upgrade investments recommended in the EPCs. We were not able to confirm how the costing of these recommendations is done. We thereby convert the estimates of the costs for specific measures, which typically include an upper- and a lower-bound range, to a further upper and lower bound based on an inflation rate estimate.

To do so, we construct a version of the cost estimate that is expressed in current GBP which effectively uprates the upper- and lower-bound cost estimate by what we judged to be the most appropriate inflation rate from the lodgement date (the date the EPC was drawn up) to the current date.

E Bounding the what, who, and how

It is inherently challenging to separate the drivers of energy consumption. Naturally, there is an interaction across at least three factors:

$$E_{i,p} = f(\text{What}_p, \text{Who}_{i,p}, \text{How}_{i,p})$$

We leverage anonymized meter-reading data from England and Wales at the property-level to bound the extent to which we can explain variation in energy use between the What_p. In the NEED anonymized microdata we observe a range of property characteristics that could drive variation in energy demand.[10] We characterise the extent to which we can capture variation in the observed energy consumption data across properties (or households) saturating simple linear regression specifications of the form

$$E_{i,p,t} = x_{i,p,t} \times \beta + \epsilon_{i,p,t}$$

The features in $x_{i,p,t}$ include:

[10]The data are a stratified random sample from the population of properties. Unfortunately, BEIS does not make the sampling weights available for each strata, which means we can not correct for the respective under- and oversampling. We have requested this information but are still awaiting a response.

- Property characteristics: property type (six categories) such as detached, semi-detached, or flat; property age band (four bands) capturing the date range when a property was built; an indicator for whether gas is the main heating fuel; floor area bins (five categories) ranging from less than 50 square meters to over 200 square meters. Further, we also have measures capturing whether a property has had some energy efficiency measures such as cavity wall insulation or loft insulation installed.

- Socio-economic characteristics: quintiles of the English and Welsh indices of Multiple Deprivation (IMD) from 2019 and council tax bands. That is, for every property, we know the region (10 regions make up England and Wales) and whether a property falls into a region in a specific quintile of the English- or Welsh deprivation ranking.

In addition, we have a property identifier which will serve as a *property fixed effect* in some specification as the most demanding, but also least informative, way of trying to absorb property- and time-invariant resident-specific observable and unobservable characteristics.

To allow for potential non-linear interactions between different property characteristics driving energy consumption such as an interaction between floor area and property age, we construct a measure that captures the unique combinations of each of the property characteristics. That is, each unique combination of property characteristics is identifying an own *group* which we refer to as `Property`. There are 9,846 unique combinations in the data of these characteristics.

We follow the same procedure for the socioeconomic indices to exploit typical patterns of socio-economic segregation in residential choice. As with property characteristics, we combine these into a group variable that captures all unique combinations that exist in the data. We refer to this as `Socioeconomics`.

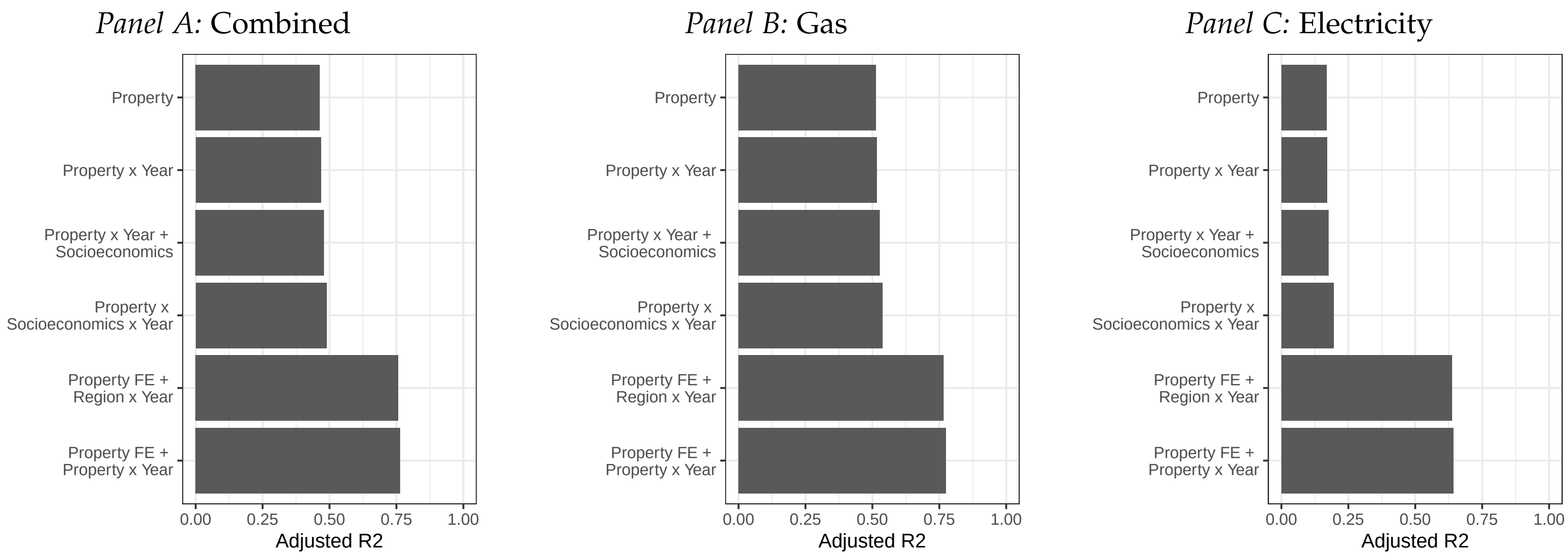
Lastly, we interact each of these variables with year fixed effects to allow for non-linear interactions of property characteristics and year-on-year unobservable shocks.

Results. We present the results from this characterisation exercise by plotting the estimated *adjusted* R^2 in Figure A6 showing both combined gas and electricity, along with gas and electricity consumption separately. We note that property and socio-economic characteristics can, at most, capture 50% of the variation in energy consumption. In particular, electricity consumption appears much more idiosyncratic compared to natural gas consumption. This finding is not surprising given that demand for natural gas is predominantly driven by space-heating and hot-water generation which do not vary much with household composition and tastes compared to electricity consumption. We note that the adjusted R^2 can reach up to around 75% in the specifications with property fixed-effects.

Interpretation. The results of this characterisation exercise suggest that property characteristics alone cannot explain much of the variation in energy demand. At most, characteristics can explain around 50% of the variation in residential energy use. Moreover, the maximal goodness-of-fit attainable appears to be bounded around 75%, obtained when we control for property fixed-effects, which may capture some of the underlying unobservable socio-economics factors (who lives there) along with behavioural factors (how do they live).

Interestingly, our validation exercise for the property-level energy demand measure we constructed produces a goodness-of-fit vis-a-vis statistical moments such as the mean and in particular, the median, that also achieves an adjusted R^2 of around 75%. This provides us with further confidence that our energy demand measures can do a good job at picking up variation in the data.

Figure A6: Decomposition of variance in the anonymized individual property-level energy consumption data documenting to what extent different features can characterise the variation in energy consumption



Notes: Figures plot out the adjusted R^2 obtained from regressing combined, gas, and electricity anonymized property-level consumption data against a set of features.

F Data used for correlational analysis

The following covariates were sourced from the 2011 UK census:

Category	Covariates
Demographics	Highest qualification obtained, ethnicity, county of birth, age, household size, self-reported health, disability
Housing	Tenure, population density, dwelling type, method of commute
Economic activity	Economic activity, industry of employment (2007 SIC)

These data were supplemented by the following variables:

Household income. Model-based income estimates at the MSOA-level are produced by the Office of National Statistics (ONS).[11] Our analysis used estimates of average total annual income for the year 2018.

Fuel poverty. Annual statistics on the number of individuals in fuel poverty at the LSOA-level are produced by the Department for Business, Energy & Industrial Strategy (BEIS).[12]. These adopt the Low Income Low Energy Efficiency (LILEE) metric of fuel poverty, which considers a household fuel poor if it lives in an energy inefficient property and has disposable income below the poverty line. Our analysis uses figures for the year 2020. These were aggregated from Lower Layer Super Output Area (LSOA) level to the MSOA level using population estimates.

Median house prices. Data on median house prices by MSOA are published by the ONS, calculated using open data from the HM Land Registry.[13] Our analysis uses figures for the year ending March 2022.

[11]Data are avaliable here `https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/smallareaincomeestimatesformiddlelayersuperoutputareasenglandandwales`

[12]Data are avaliable here `https://www.gov.uk/government/collections/fuel-poverty-sub-regional-statistics`

[13]Data are avaliable here `https://www.ons.gov.uk/peoplepopulationandcommunity/housing/datasets/hpssadataset2medianhousepricebymsoaquarterlyrollingyear`

Index of Multiple Deprivation (IMD). English Indices of Deprivation (IoD) are published by the Department for Levelling Up, Housing & Communities.[14] These are relative measures of deprivation which incorporate the seven following domains: income; employment; health deprivation and disability (in our analysis, we refer to this as health); education, skills and training (education); crime; barriers to housing and services (housing and services) and living environment. Our analysis uses rankings along these dimensions for each LSOA for the year 2019. These were aggregated to the MSOA-level using population estimates.

[14] Data are available here `https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019`