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Unequal carbon tax impacts on 38 million German households: assessing spatial and socio-economic hotspots

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Supplementary material for this article is available online

Abstract

Carbon pricing is a core climate policy in many countries. However, the distribution of impacts is highly unequal across income brackets, but also across household types and regions. The complex interplay between household characteristics and location specific factors such as building stock and transport infrastructure considerably hampers our understanding of the inequality impacts of carbon taxes and the development of remedial measures. In this paper, we simulate the impacts of carbon taxes and compensation on the purchasing power of more than 38 million German households living in over 11 000 municipalities. We find that the strength of impacts varies more within income groups (horizontal inequality) than across income groups (vertical inequality), based on demographic, socio-economic and geographic factors. Without compensation, a carbon tax of €50 per ton doubles the number of households at risk of becoming energy poor, the majority of them low-income families in remotely located small and medium cities. A lump sum payment of €100 per capita and year reduces inequality impacts and additional energy poverty risk substantially.

1. Introduction

The goal of carbon taxes on fossil fuel purchases is to reduce carbon emissions by creating incentives to reduce fossil fuel consumption in the short term and to encourage the adoption of more energy- and carbon-efficient technologies in the medium to long term (Metcalf 2009, Edelstein and Kilian 2019, Green 2021, Lilliestam *et al* 2021). The role that direct pricing of CO_2, e.g. in the form of a carbon tax, can or should play in achieving the Paris climate goals is controversial in the political and scientific debate. Some see it merely as an accompanying measure to a comprehensive program of direct fiscal and monetary strategies to transform the economy while expanding social provisioning systems, while others ascribe to it the main role in decarbonizing the economy. Relying primarily on carbon pricing, estimates suggest that a carbon price of \$40–\$80 ton^{-1} CO_2 by 2020 and \$50–\$100 ton^{-1} CO_2 by 2030 (the so-called 'carbon price corridor') would be necessary to meet the goals of the Paris Agreement (Carbon Pricing Leadership Coalition 2017, Schipper *et al* 2022). Although carbon prices reached record highs in many countries in 2021, most carbon prices remain well below this price corridor (World Bank 2022).

Ramping up national carbon prices is politically difficult because of concerns about carbon leakage and loss of economic competitiveness of energy intensive and trade exposed businesses (Aldy and Pizer 2015, World Bank 2015, Venmans *et al* 2020), and about the regressive effects of carbon prices (Ürge-Vorsatz and

Tirado Herrero 2012, Klenert *et al* 2018, Pizer and Sexton 2019), i.e. low-income households are taxed on a larger share of their household income than high-income households (Flues and Thomas 2015, Williams *et al* 2015). As electricity, heating and mobility are necessities that poorer households spend a larger share of their budgets on, demand elasticity is low and even modest price increases can drive poor households into energy poverty. Also, the technologies available to poor households are often less energy- and carbon-efficient and their ability to invest in cleaner technologies is very limited (Goldstein *et al* 2020, Ivanova and Wood 2020, Jaccard *et al* 2021). Therefore, there is broad agreement that the necessary increases in carbon prices need to be complemented by additional policies to increase acceptance and abate negative impacts on households and economic sectors (Carbon Pricing Leadership Coalition 2017, Best *et al* 2020, Schipper *et al* 2022, World Bank 2022).

Behavioral economists and political scientists emphasize the importance of distributional fairness and revenue salience, pointing to a mix of targeted transfers and green spending, such as subsidies for renewable household energy or electric vehicles (Kallbekken *et al* 2011, Klenert *et al* 2018, Baranzini and Carattini 2017, Malerba and Wiebe 2021). However, designing well-targeted revenue recycling policies need a solid evidence base to derive clear criteria for identifying households in need of transfers, especially those who are at risk of suffering from poverty, including energy poverty. Recent evidence suggests that the regressive effects of carbon pricing are not simply a function of the income distribution. In fact, the variance of impacts of rising energy prices on households within income groups (horizontal inequality) can be greater than between income groups (vertical inequality) (Flues and Thomas 2015, Rausch *et al* 2011, Klenert and Mattauch 2016, Reaños and Wölfing 2018, Cronin *et al* 2019). In addition to income, distributional effects depend on: (1) which fuels or energy technologies are taxed, (2) the location and characteristics of a region and its population, including car dependence (Creutzig *et al* 2015, Mattioli *et al* 2020) and settlement structure (Grubler *et al* 2012, Minx *et al* 2013), (3) the energy efficiency of buildings, appliances, and motor vehicles (Ürge-Vorsatz and Tirado Herrero 2012, Goldstein *et al* 2020, Ivanova and Wood 2020, Jaccard *et al* 2021), and (4) how tax revenues are redistributed (Cronin *et al* 2019, Pizer and Sexton 2019, Metcalf 2021).

The complex interlinkages of those factors are typically not known for entire national economies at the spatial and socio-economic granularity required to develop targeted economy-wide carbon or energy price abatement policies. Therefore, governments that wish to shield vulnerable households from energy poverty caused by energy price spikes, whether because of geopolitical developments or carbon pricing policies, face severe challenges. In the past years several countries have seen mass protests against carbon pricing. These protests reflect discontent with the unequal impacts of energy price increases, but also with the rising wealth and income inequality that has grown in practically every country over the past several decades (Carbon Pricing Leadership Coalition 2017, Driscoll and Blyth 2021, World Bank 2022).

This study investigates the characteristics of households that make them highly susceptible to energy price shocks, as well as their spatial distribution. We simulated 30 socio-economic and housing characteristics, including income, wealth, floor size, number, age and gender of household members, building type, heating technology, occupation, and ownership, for more than 38 million German households located in more than 11 000 municipalities covering the entire country. On this basis, we simulated the effects of a 50 Euro per ton carbon tax and two different compensation schemes on the purchasing power and energy poverty of households. Germany has indeed introduced a carbon tax of initially EUR 25 per ton on transport and heating fuels in 2021, which is to rise to EUR 45 by 2025. The carbon tax on transportation and heating fuels is intended to complement the European Union's Emission Trading System (EU ETS), which currently only covers the energy sector and industrial consumers and is expected to be extended to transportation and buildings until 2025. As compensation, taxes on electricity were reduced in 2022, but an originally planned lump-sum transfer has not been implemented yet. Both taxing and emissions trading have socio-economic impacts, even if the article focuses on taxing only.

In particular, our approach contributes to the limited evidence on vertical (across income brackets) versus horizontal (within income brackets) inequality impacts of environmental taxes (Pizer and Sexton 2019, Hänsel *et al* 2022) by allowing us to map the large heterogeneity of geodemographic factors driving horizontal inequality in much greater detail than is possible with household samples. Specifically, we examine the impact of horizontal inequality and how its heterogeneity affects the poorest households. Horizontal inequality impacts can pose a serious challenge for the design of compensation policies, as a large share of households in the lowest income bracket may not be reached by the proposed compensation policies.

2. Methods

2.1. Simulating the German population

Our simulation of more than 38 million households is based on a synthesis of household-level microdata and census counts of people, households, and dwellings for more than 11 000 communities. Synthetic population

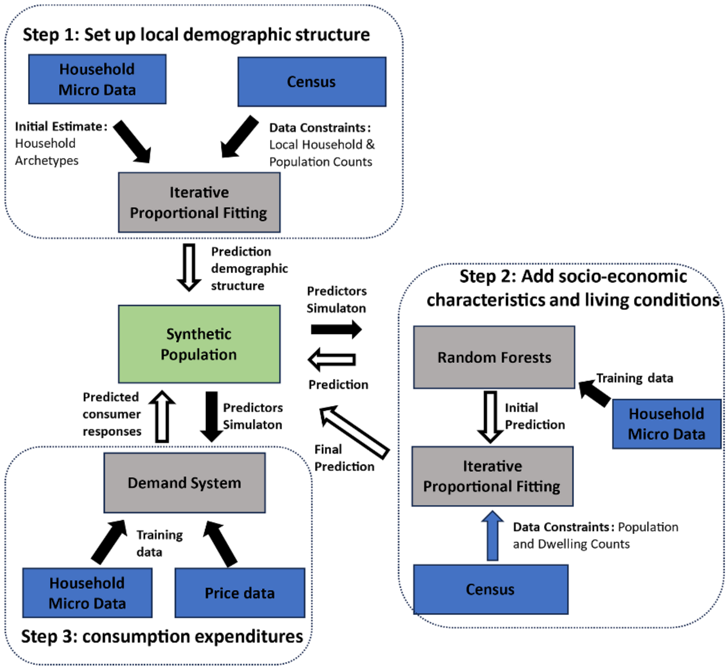

Figure 1. Model overview: the synthetic German population and demand estimation.

data sets are the backbone of data-driven social simulations (Chapuis *et al* 2022). While the microdata are used to estimate statistical interrelations between variables observed at the level of individual households, census data deliver information about the frequency of household characteristics in the regions.

As shown in figure 1, we employ different types of statistical models to estimate demographic, socio-economic and consumption variables in a stepwise manner. Following Templ *et al* (2017), in each step, variables added to the synthetic population in the previous step are used as explanatory variables. At first, we set up the local demographic structure of the synthetic population using iterative proportional fitting (IPF) algorithms (section 2.1.1). Next, we add socio-economic characteristics such as education, socio-economic status and income pattern (section 2.1.2.1), public transfers and taxes (section 2.1.2.2) as well as living conditions (section 2.1.2.3) using random forest classifiers and regressors. Finally, we estimate consumption pattern including expenditures for electricity, transport and heating fuels using an econometric household demand system (section 2.2). Our model takes demographic, socio-economic and geographic household characteristics into account to map responses to energy price and income shocks resulting from carbon taxes and revenue recycling policies.

The household microdata come from the 'Income and Expenditure Survey' (EVS for Einkommens- und Verbrauchsstichprobe) conducted by the Federal Statistical Office every five years with an average sample size of about 40 000 participants per wave. For this study, we use the waves from 1998 to 2018. Apart from detailed household income and expenditure patterns, the EVS also delivers detailed information on household structure, socio-economic characteristics of household members (age, gender, education), rural/urban typology, as well as of housing conditions, car ownership, heating system and household appliances. A detailed list of the variables used is provided in the Supplementary Information. The population counts come from the most recent census from 2011. The census not only covers the number of people, households, and apartments in each community, but also provides information on their composition and characteristics. For households, we get the number of households by size and type (singles, couples, couples with children, etc), for apartments it distinguishes space, building age, building type and the type of heating system, whereas for population, it contains detailed information on demographic (age, gender, marital status) and socio-economic characteristics (education, employment status).

2.1.1. Modeling the demographic structure in German communities

The demographic structure of the German population in 2011 at community level is generated by adjusting the empirical frequency distribution of household types and the characteristics of their members to census population counts using an IPF algorithm that allows taking both dimensions simultaneously into account (Meraner *et al* 2016). A list of the demographic variables considered here is shown in table 1. From the household microdata, we cluster about 10 000 unique combinations of the household characteristics 'household type' and 'household size', and the personal characteristics of the household members 'age',

Table 1. List of demographic variables of the synthetic German population.

Variable	Description	Person/household	Data constraint
Household	ID	h	—
Municipality	ID	h	—
Relation	1 = main income earner, 2 = partner, 3 = child, 4 = other relative, 5 = other non-relative	p	—
Age	1 = [0, 5], 2 = [6, 14], 3 = [15, 29], 4 = [30, 49], 5 = [50, 64], 6 = [65, 79], 7 = [80, Inf]	p	Community
Gender	0 = female, 1 = male	p	Community
Household size	1, 2, 3, 4, 5, 6 = 6+	h	Community
Household type	1 = single, 2 = couple, 3 = couple with children, 4 = lone parent, 5 = other	h	Community

Table 2. List of socio-economic variables of the synthetic German population.

Variable	Description	Person/household	Data constraint
Education	1 = non, 2 = vocational training, 3 = vocational college, 4 = bachelor, 5 = master, 6 = PhD	p	Community
Socio-economic status	1 = dependent employee, 2 = self-employed, 3 = official, 4 = unemployed, 5 = inactive	p	Community
Industry	NACE codes: 0 = non, 1 = A, 2 = BtC, 3 = DtE, 4 = F, 5 = GtH, 6 = ItJ, 7 = K, 8 = LtN, 9 = O, 10 = PtU	p	Community
Worktime	Hours week^{-1}	p	—
Wage	€ h^{-1}	p	—
Labor income	Computed variable: worktime * wage	p	County
Property income	€	p	—
Non-public transfers	Computed variable: worktime * wage	p	—
Primary income	Computed variable: household labor income + property income + non-public transfers	p	County

'gender' and 'relation', to generate archetypes (Froemelt *et al* 2020). For each archetype, the case weights delivered with the household microdata show how frequent that archetype in the German population is. The IPF algorithm is applied at the level of communities, and minimizes the information distance between the local frequency distribution of archetypes from the national one, subject to census population counts. Afterwards we sample households by size and type, for each community, from the respective adjusted frequency distribution. The adherence of the demographic variables of the synthetic population to the census data is shown in the supplementary information.

2.1.2. Socio-economic characteristics and living conditions

The variables describing socio-economic characteristics and living conditions of households are sampled one after another, in each step using the variable from the previous step as a covariate for the next prediction. A list of the socio-economic and living conditions variables is shown in table 2. We train random forests (Malley *et al* 2012) to learn the class probabilities of each socio-economic variable conditional on the household's or person's geo-demographic and remaining socio-economic variables. We then use these random forests to predict the respective class probabilities learned from the microdata on the persons or households in the synthetic population. For many variables to be predicted we have census counts at the community or county level. In this case, we adjust the predicted class probabilities of the synthetic population to these census counts using IPF before we sample the class for each person or household. Overall, the estimation is carried out in three steps, one for each block of variables. In the supplementary information, we show the importance of covariates and prediction errors in each of the random forests, as well as confusion matrices showing actual versus predicted class probabilities. For those variables subject to data constraints, we also show the adherence of the synthetic population to the data. As dwelling characteristics and car ownership are of particular importance for household's energy consumption and response to the tax, we additionally compare the distributions of these variables across region income, region size and demographic group between the microdata sample and the predictions of the synthetic population.

2.1.2.1. Socio-economic characteristics and primary income

Among the socio-economic characteristics, the household microdata sample distinguishes educational attainment, socio-economic status, the industry of employment, worktime, and wage as person-level

Table 3. Public transfers and deductions from income in the synthetic German population.

Variable	Description	Person/household	Data constraint
Pensions	€	p	—
Unemployment benefits	€	p	—
Family benefits	€	h	—
Education grants	€	p	—
Basic social security	€	h	—
Public transfer income	Computed variable: pensions + unemployment benefits + family benefits + education grants + basic social security	h	County
Income taxes	€	p	—
Social security deductions	€	p	—
Other taxes	€	h	—
Disposable income	Computed variable: primary income + public transfers − income taxes − social security deductions − other taxes	h	County

Table 4. Dwelling characteristics and equipment with durable goods in the synthetic German population.

Variable	Description	Person/household	Data constraint
Owner	0 = tenant, 1 = owner	h	Community
Building age	1 = before 1948, 2 = [1948, 1990], 3 = [1991, 2000], 4 = after 2001	h	Community
Building type	1 = one-family house, 2 = two-family house, 3 = apartment building/other	h	Community
Dwelling size	m^2, 1 = [0, 40], 2 = [41, 60], 3 = [61, 80], 4 = [81, 100], 5 = [101, 120], 6 = [121, 140], 7 = [141, 160], 8 = [161, 180], 9 = [181, 200], 10 = [200, Inf]	h	Community
Heating system	1 = district heating, 2 = central heating, 3 = other	h	Community
Heating fuel	1 = electricity, 2 = gas, 3 = liquid fuels, 4 = solid fuels, 5 = other	h	—
Cars	0, 1, 2, 3 = 3+	h	—
Motorcycles	0, 1, 2, 3 = 3+	h	—
Appliances	0 = 2 or less, 1 = 3, 2 = 4, 3 = 5, 4 = 6, 5 = 7 or more	h	—
Consumer electronics	0, 1, 2, 3, 4 or more	h	—
Communication equipment	0, 1, 2, 3, 4 or more	h	—

variables, as well as property income and income from non-public transfers as household-level variables. For continuous income variables, we first compute deciles and let the random forest learn the class probabilities of a person or household conditional on the geo-demographic and socio-economic characteristics. In the synthetic population we first predict the decile and afterward sample continuous income from a uniform distribution bounded by the decile breaks. For the first three, we have corresponding population counts from the census at community level. The sum labor-, property- and non-public transfer income constitutes primary income, about which we have data constraints at the county level. Since the order by which we predict the variables from one another can be important, especially for the socio-economic variables (i.e. predict earnings from education or vice versa), we follow the strategy from Sun and Erath (2015) and re-iterate for these variables such that in the final round each socio-economic variable is predicted by all the other socio-economic variables.

2.1.2.2. Public transfers, deductions, and disposable income

We distinguish five types of public transfers, namely pensions, unemployment benefits, family benefits, education advancement grants, and basic social security, and consider that these transfers are highly dependent on the socio-economic characteristics of households and household members, i.e. only unemployed persons receive unemployment benefits. A list of variables on public transfers and deductions from income are shown in table 3. As for the components of primary income, we group households receiving a specific public transfer into deciles in the microdata to learn class membership using random forests. Basic social security transfers, finally, are computed as the residual between total income and the official subsistence level. Deductions from income are modeled differently, in that we transform the payments into shares in the respective income base of that deduction. Social security deductions are modeled as shares in gross labor income of a person, whereas income taxes are modeled as shares in gross labor income less social security deductions. Other household taxes are based on total income of households excluding labor income. After estimating the public transfers and deductions, we can compute the disposable income of households as the sum of primary income and public transfers less deductions. As for primary income, data constraints on total disposable income are available at the county level.

2.1.2.3. Dwelling characteristics and equipment with durable goods

Dwelling characteristics and the equipment with durable goods, such as cars or household appliances, are important determinants of a household's energy consumption (Sommer and Kratena 2017). A list of variables on dwelling characteristics and durable goods is shown in table 4. The dwelling characteristics are important determinants of heating energy consumption. Here, we distinguish age and type of the building as proxies for quality of the building insulation, as well as dwelling space, as a main determinant of heating demand and type of heating system, as a determinant for the efficiency by which heating fuels are transformed into useful energy. For these variables, there are data constraints available at the community level from the census, and the predicted class probabilities are adjusted to census counts (i.e. number of apartments) using IPF. Furthermore, we distinguish four types of heating fuels, namely gas, oil, and solid fuels as well as renewable energies. Among the different types of durable goods, the ownership of cars and motorcycles determines whether a household consumes transportation fuels and the equipment with household appliances, consumer electronics and communication equipment are important determinants in estimating a household's electricity consumption.

2.2. Estimating consumption expenditures and price elasticities

2.2.1. Total expenditures

To measure the capability of individual households to cope with price changes and compensation policies, it is more useful to consider impacts relative to disposable income rather than total expenditures, thus taking savings into account. Rich households generally have a much higher saving rate compared to poor households, whose consumption expenditures often exceed their disposable income.

We assume the share of total (nominal) consumption expenditures, in disposable income, $c = 1 - \text{saving} = \frac{X}{inc}$ as a function of a polynomial of the log of disposable income *inc*, prices *P* and household characteristics z_l, i.e.

$$c = \iota + \sum_{r}^{R=4} \kappa_r \log(inc)^r + \lambda \log(P) + \nu_l z_l + \xi \log(inc) \log(P) + \rho_l z_l \log(inc) + \tau \log(P) + \in . \quad (1)$$

We, furthermore, consider interactions between consumer price index (CPI), income and household characteristics, whereby the latter we restrict to demographic characteristics, city size and home ownership. Detailed estimation results can be found in the supplementary information.

2.2.2. Budget shares and consumer responses

Consumer expenditures of households are modeled by means of the econometric Exact Affine Stone Index (EASI) demand system (Lewbel and Pendakur 2009). Demand systems are simultaneous equation models, where each equation represents the budget share in an expenditures category, while the setup as a system allows to model substitution between categories taking household budget restrictions into account. The expenditure categories follow 'The Classification of individual consumption by purpose', COICOP. The EASI demand system constitutes the most recent development in this class of models and has proven its capability to capture the vast heterogeneity in household consumption patterns. We estimate the demand system for seven aggregate consumption categories: food, housing, electricity, heating, fuel and other goods and services. It takes the following form:

$$s_i = \alpha_i + \sum_{r=1}^{R=4} \beta_{i,r} \log(y)^r + \sum_j \gamma_{i,j} \log(p_j) + \sum_l \delta_{i,l} z_l + \zeta_i \log(y) \log(p_j) + \sum_l \eta_{i,l} \log(y) z_l + \sum_l \theta_{i,l} \log(p_j) z_l + \in_i . \quad (2)$$

The budget share in COICOP category *i* depends on (a) real total expenditures *y* as a measure for wealth, (b) the price of goods and services in the same category ($i = j$), as well as on the prices of other COICOP categories ($i \neq j$) and (c) dummy variables, z_l controlling for household characteristics. In addition, we consider interaction terms between (d) total expenditures and prices, (e) total expenditures and household characteristics, as well as (f) prices and household characteristics.

For real total expenditures we use a polynomial of up to the fourth degree, to allow for flexible Engel curves describing the relationship between budget shares and income. In this paper, we use the linear approximation of the generally non-linear EASI demand system, which means that real total expenditures are defined $y = \frac{X}{P}$, where X denotes total nominal consumption expenditures and $\log(P) = \sum_i s_i \log(p_i)$ denotes the stone price index.

As dummy variables controlling for household characteristics, we consider demographic characteristic (age, household size and type), geographic characteristics of the residence (federal state, city size, number of heating degree days), time (year, quarter) as well as living and housing conditions (home and car ownership, space, building age, number of household appliances and heating energy carrier).

The interaction terms between total expenditures, prices and the dummy variables. The price interactions with total expenditures and the dummy variables are of particular importance in this study. They allow the capture of heterogeneity in price responses across households, such that we receive individual price and income elasticities for any combination of income and the dummy variables. We restrict the interactions between the dummies and prices to variables that we expect to have a significant impact on a household's ability to respond to price shocks. These are the demographic characteristics, city size, home and car ownership, and heating energy carrier.

2.2.3. Data, processing and estimation

Similar to Pothen and Reaños (2018), the parameters of the EASI demand system are estimated from the EVS data, the waves for 1998, 2003, 2008, 2013 and 2018, which provide information on consumer expenditures, income, and household characteristics. After filtering for households with outliers (i.e. outside 1.5 times the interquartile range above the upper quartile and below the lower quartile) in the budget shares, we have about 180 000 observations for the estimation.

For prices, we use monthly CPIs at the national level at four-digit COICOP group resolution. A frequent challenge for the estimation of demand systems using cross-section data, constitutes the low variance in the price data. Since each EVS wave is subdivided into quarters, there are only 20 different price observations per COICOP category. Since we estimate the demand system for seven aggregate consumption categories, we apply Lewbel's method (Lewbel 1989). Household specific prices for the seven aggregate consumption groups are computed as weighted averages of national CPIs at four-digit resolution, and respective shares of the subcategories in a household's basket reported in the EVS. Exceptions are made for electricity, which only consists of a single subcategory, and for housing, where we compute rents (actual and imputed) per square meter from housing expenditures and apartment space. As an additional explanatory variable, we use the average number of heating degree days by quarter and federal state provided by Eurostat.

We estimate the linear approximation of the EASI demand system rather than the original nonlinear version, which requires specific iterative solution routines. The linear version by contrast can be estimated as a seemingly unrelated regression model, where interactions between equations are captured by allowing for correlated error terms across equations. Detailed estimation results are provided in the supplementary information.

2.3. Simulations and impact metrics

2.3.1. Simulating demand responses to price and income changes

The demand responses to price and income changes due to the carbon tax and possible compensation policies are modeled by means of own-price and expenditure elasticities. We do not consider cross-price effects in this study. The elasticities measure the percentage change in demand for good i due to a one percent change in price or in total expenditures, respectively.

The own-price elasticities (OPEs) of consumption category i are computed from equation (1) as

$$OPE_i = \left\{ \frac{\partial s_i}{\partial \log p_i} \frac{1}{s_i} \right\} - 1 = \frac{\left(\gamma_i + \zeta_i y + \sum_l \theta_{i,l} z_l - 1 \right)}{} \tag{3}$$

and are a function of wealth y, household characteristics z_l and the budget share s_i. Similarly, the total expenditures elasticity is computed as

$$EE_i = \left\{ \frac{\partial s_i}{\partial \log y} \frac{1}{s_i} \right\} + 1 = \frac{\left(\sum_r^{R=4} r \beta_{i,r} y^{r-1} + \zeta_i p_i + \sum_l \eta_{i,l} z_l + 1 \right)}{} \tag{4}$$

and, additionally, depend on the price of i. We use these formulas to compute elasticities specific for each household h in the synthetic population data set by, first, predicting budget shares $s_{i,h}$ using equation (1) and the variables in the synthetic population dataset. For prices we again use national CPI data for 2011 (the census year to which the synthetic population is calibrated). To capture spatial housing price differentials, which make out most overall spatial price differences, we use data at county level from (Weinand and Auer 2020).

2.3.2. Estimating household's energy consumption in physical units

Since our simulated data set maps the entire German population, we allocate total national consumption of heating energy and transportation fuels according to household h's expenditure share in total national expenditures, i.e.

$$e_h = E_{\text{national}} \frac{x_h}{\sum\limits_h x_h}. \tag{5}$$

National household consumption of heating gas and oil was taken from the German environmental economic accounts (Destatis 2021), and consumption of transportation fuel was computed from annual consumption for private transportation of gasoline and diesel in liters (BMDV 2022), weighted by their specific caloric values.

2.3.3. Loss of purchasing power

We measure the impact of the tax, and of possible compensation policies, on the individual household by means of changes in purchasing power, i.e. the ability to consume. Therefore, we need to take the saving rates of households into account which can be used to compensate for an increase in the cost of living. For this reason, we compare real disposable income under the different scenarios. We use 0 and 1 to denote variables in the base and the alternative scenarios, respectively, i.e. before and after price changes due to carbon taxes and compensation policies, $\Delta p_{i,h}$.

$$\Delta pp_h = c_h^0 - \frac{c_h^1}{1 + \sum_i c_{i,h}^1 \Delta p_{i,h}}, \tag{6}$$

where $c_{i,h}^1$ denotes the share of expenditures for i in disposable income in the alternative scenarios, i.e.

$$\Delta c_{i,h}^1 = \frac{x_{i,h}^1}{c_h^1} = \frac{x_{i,h}^0 (1 + \Delta p_{i,h})^{OPE_h} (1 + \Delta y_h)^{EE_h}}{c_h}. \tag{7}$$

3. Results

Based on a synthesis of household-level microdata and census counts of persons, households, and apartments for over 11 000 municipalities, we created a synthetic population of 38 million German households that is representative of the whole German population. While microdata are used to estimate statistical relationships between variables observed at the level of individual households, census data provide information regarding the frequency of household characteristics in municipalities. The microdata are from five waves between 1998 and 2018 and the census data from 2011.

Consumer responses to these price increases are modeled using OPEs, which measure the percentage decrease in consumption volumes in response to a one percent price increase. We estimated the OPEs from the household level microdata underlying the synthetic population, using an econometric demand system. Individual household elasticities depend on the combination of different household characteristics, in particular the income level, household type (family, single/couples, old single/couples), region size, and location, as well as type of heating energy (for heating) and car ownership (for fuel).

Our scenario specifications of the carbon tax and compensation policies follows Edenhofer *et al* (2019). Considering other taxes on fossil fuels, a carbon tax of EUR 50/tCO_2 is estimated to lead to price increases of 6.7% for natural gas, 14.5% for heating oil, and 13.4% for fuels. To compensate households for the increase in living cost, we assume the German government is implementing a per capita lump sum transfer and abolishing the Renewable Energy Sources Act (EEG for Erneuerbare Energien Gesetz) levy on electricity prices. For the lump sum transfer we assume 100 EUR per person and year. This amount leads to a revenue neutral compensation of households (i.e. the sum of tax revenues from households equals the sum of transfers to households) and follows the idea that a person who emits exactly their carbon budget of roughly two tons per year (Jaccard *et al* 2021) faces a net-effect of zero on purchasing power. The EEG levy was formerly used to finance the expansion of renewable energies in Germany, but was abolished by the German government in 2022. All things being equal, cutting the EEG levy reduces the household electricity price by about 14%.

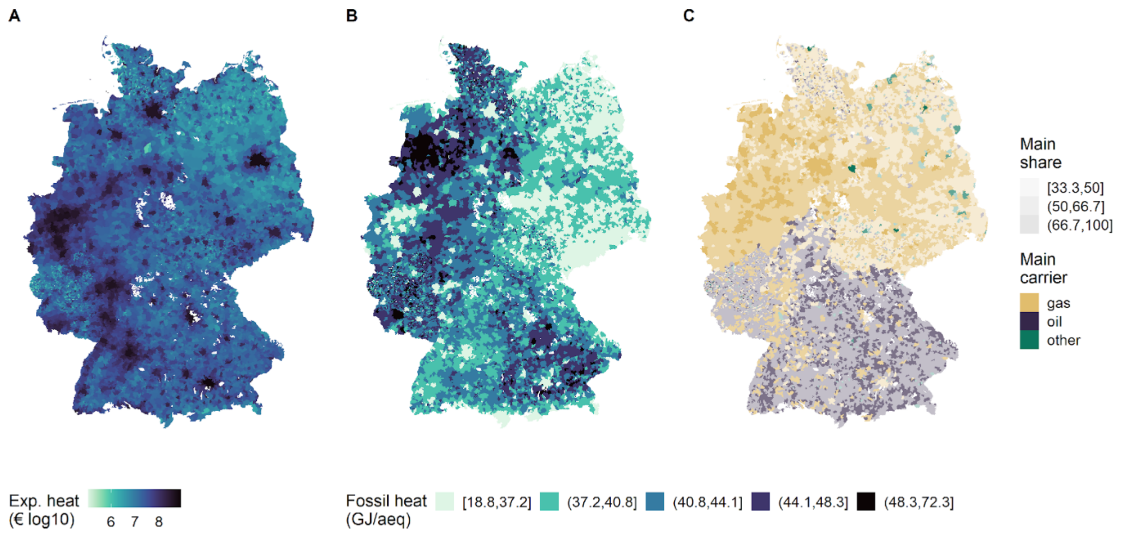

Figure 2. Heating in German households: (A) total overall heating expenditure (all energy carriers), (B) mean fossil energy (oil and gas) use for heating per adult equivalent of households using fossil heat, and (C) main energy carrier (oil, gas, other) used and share of households using it.

3.1. Energy use for thermal services and private motorized mobility by German households

German households consumed 2077 PJ of final energy (Arbeitsgemeinschaft Energiebilanzen 2021) for heat (space, water, and other) in 2019. Figure 2(A) provides an overview of the geographical distribution of the total expenditure for thermal energy (all energy sources) of German households at the municipal level. This mainly serves to demonstrate where in the country the building stock and the population are concentrated. The middle map (figure 2(B)) shows fossil fuel consumption (i.e. gas and oil only) per adult equivalent in households that heat with gas or oil. Adult equivalent units are designed to normalize household variables, such as income, energy use, etc, to different household sizes (OECD 2008). Differences in fossil fuel consumption for heating are mainly due to differences in used living space, thermal characteristics of the buildings, efficiency of the energy source, and individual differences in heating comfort and hot water consumption. The third map (figure 2(C)) shows which energy source (oil, gas, or other) is used most in each community. As can be seen, gas is still the dominant energy source for heat supply in Germany. Especially in cities (see population centers in figures 2(A) and (C)) and in the northern part of the country, gas by far dominates heating energy. In sharp contrast, in rural areas in the south (Bavaria and Baden–Württemberg) many communities are not connected to the gas grid (Destatis 2019) and use oil as their main energy source. Overall, almost half (48.9%) of households use gas (1073 PJ) and a quarter (25%) use oil (450 PJ), and would thus be affected by a carbon tax on emissions related to direct energy consumption. The differences in energy intensity per adult equivalent as shown in figure 2(B) are mainly driven by income differences (partly responsible for the differences between the former Federal Republic of Germany (FRG) and the former German Democratic Republic (GDR)), energy efficiency differences between oil and gas (gas is more efficient), floor space, itself a function of housing prices and income (responsible for the rural–urban divide), and the energetic quality of the buildings.

Comparing the local individual transport fuel consumption per adult equivalent with the local income and size of settlements (figures 3(A) and (B)) shows that the highest fuel consumption is concentrated in the wealthy rural regions of the South and the extreme north. The central income gradient in Germany is still between the old FRG and the former GDR, not between urban and rural areas (measured by community size class) (figure 3(B)). The highest incomes are concentrated in the south of Germany, regardless of the size of the municipality, and in most of the country's large cities, and their surrounding medium-sized municipalities. More than three decades after reunification, Berlin remains an oddity among world capitals as a middle-income city. With a median of 89.7%, the car ownership rate (figure 3(C)) is generally very high in Germany. Significant downward deviations can only be observed in large cities with more than 500 000 inhabitants (figure 3(C)).

3.2. Household response to a carbon tax on gas, heating oil and transportation fuels

Based on our calculated OPEs, German households would respond to an unmitigated carbon tax of €50/t by reducing their total energy consumption for heating by 92 PJ (or −6%) in total. For gas, consumption would fall by 39 PJ (or −3.6%) and for oil by 53 PJ (or −11.8%). The response is much stronger in small and

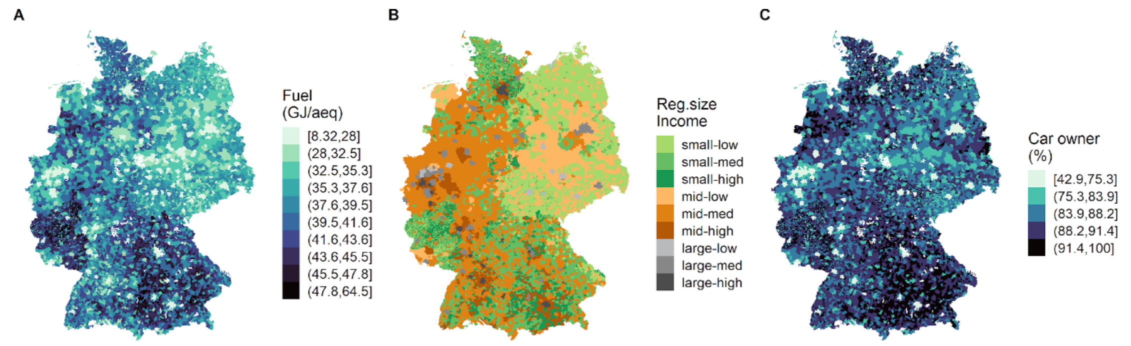

Figure 3. Transport fuel use in German households: (A) mean fuel use for individual private transport per adult equivalent, (B) community size and income, and (C) levels of car ownership across communities.

medium-sized communities in the south of the country than in the north and in large cities (figure 4(A)). This is mainly due to the predominant use of heating oil in rural communities in the south (figure 2(C)) and the significantly higher OPEs for oil (figure 4(B)) than for gas. The reason for the generally stronger household response to oil price increases is the stronger effect of the carbon tax on oil as compared to gas (14.5% vs. 6.7% price increase due to carbon tax for oil vs. gas, respectively). In addition, for oil the response is similarly strong across all expenditure deciles (−0.99 to −0.91 range) while for gas it decreases significantly with increasing expenditure decile (−0.76 to −0.48 range). The reason for this could be the different purchasing modalities for the two energy sources. While oil can be bought and stored opportunistically in large quantities when prices are favorable, gas is usually billed monthly according to consumption. For both fuels, homeowners react less strongly than renters (−6.9% and −8.5% difference for gas and oil, respectively), given the same income.

Comparing the reductions in energy use across heating fuels, we find substantial reductions in oil use for high-income households and here especially for singles and couples, although gas is the dominant heating fuel overall (figure 4(C)). We explain this pattern, on the one hand, by a combination of more elastic price responses for oil and the larger price increase due to the tax. On the other hand, differences in lifestyles are an important factor, as high-income households are much more likely to live in single-family houses, which are more likely to be heated with oil than multi-family houses. Comparing gas and oil consumption in small cities we find that the absolute reduction in energy use strongly reflects the dominance of oil in the rural areas of southern Germany. Finally, we find distinct patterns of energy use reductions across expenditure deciles for families and younger singles/couples as opposed to elderly singles and couples. In the first case, we observe the strongest absolute reductions of heating energy consumption for families in the ninth decile, and for younger singles/couples in the fifth decile. For elderly singles/couples, the reduction in heating energy consumption grows monotonically with income.

In response to a 13.4% carbon tax on fuel, German households would reduce their consumption by 9.2% (from 1682 to 1540 PJ). However, the responses of households within the same income decile differ considerably, depending on community size and household type, as well as large differences in pre-tax gasoline consumption between these groups (figure 5(B)). These outcomes are in line with findings of other research on horizontal inequality impacts of carbon taxes Flues and Thomas 2015, Rausch *et al* 2011, Klenert and Mattauch 2016, Reaños and Wölfing 2018, Cronin *et al* 2019).

In large cities, the absolute savings of most households are at or below the median. This is due to relatively lower consumption and car ownership rates compared to smaller communities. Across income deciles, there is a saturation point in large cities, where absolute savings no longer increase with rising income (or even decrease again in the 10th decile). This is especially true for families and the elderly, for whom this effect can still be observed in medium-sized municipalities. In small communities (with higher baseline consumption per adult equivalent), the absolute savings are consistently larger and more linearly related to the income decile. Wealthy young singles and couples have the highest absolute savings potential across the board.

Many countries recognize energy poverty, which is characterized by an inability to meet basic energy needs and is distinct from general poverty (Sovacool 2012, Pelz *et al* 2018). In middle- and high-income countries, energy poverty typically results from arrears on utility bills and leads to serious health consequences and social isolation (Thomson *et al* 2017). A widely used indicator to measure energy poverty is the share of disposable income spent on energy. First defined for the UK (Boardman 1991) as twice the share of expenditure on electricity and heating for the median household, the 10% threshold, has been widely adopted in other countries. We use an extended version of this metric that also includes car fuels (Mayer *et al* 2014, Drescher and Janzen 2021). Households above the threshold are assumed to be at risk of

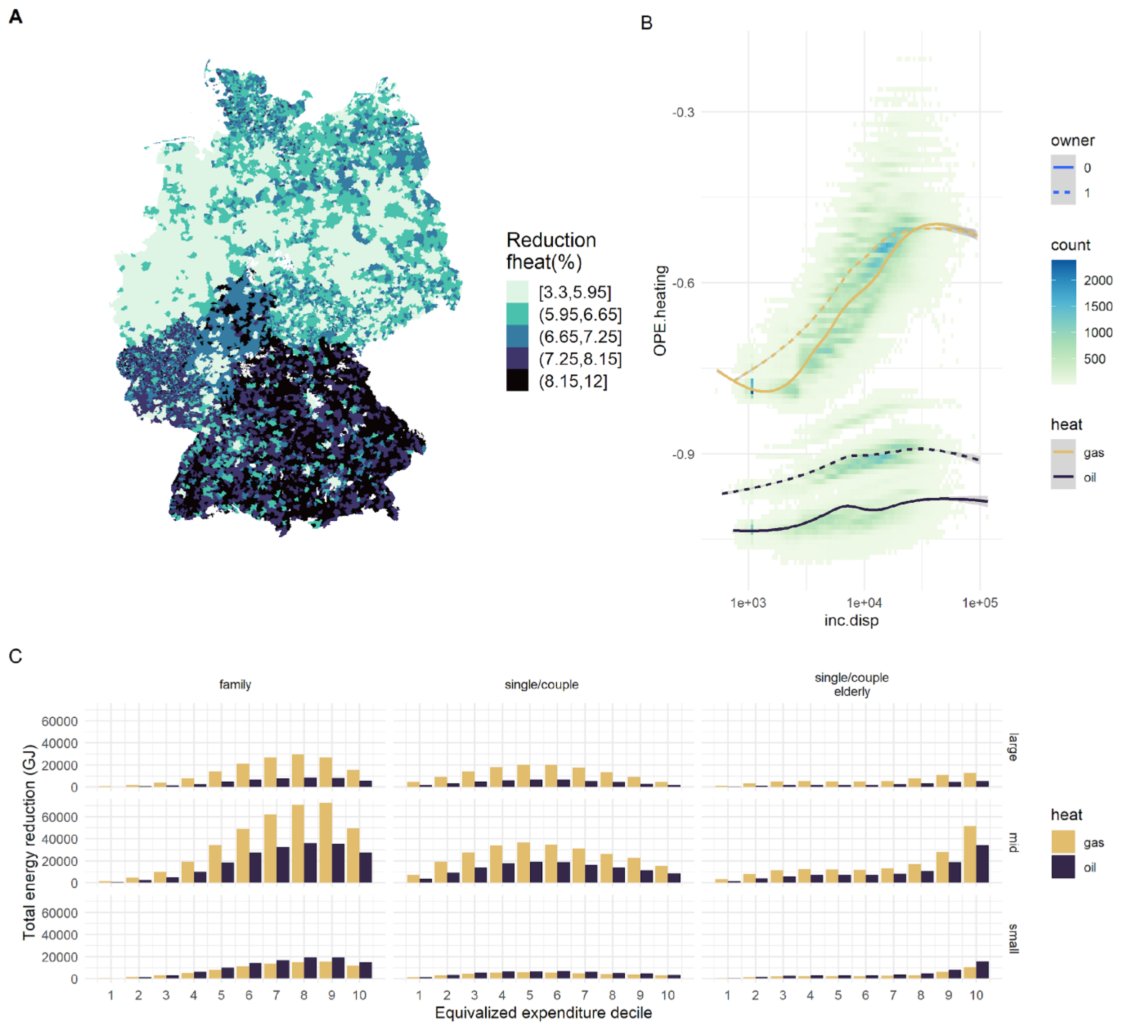

Figure 4. Heating energy use response to carbon tax: (A) relative reduction of heating energy use, (B) own price elasticities by expenditure decile for oil and gas, differentiated by owner status of household, (C) total reduction in energy use disaggregated by energy carrier, community size and household type.

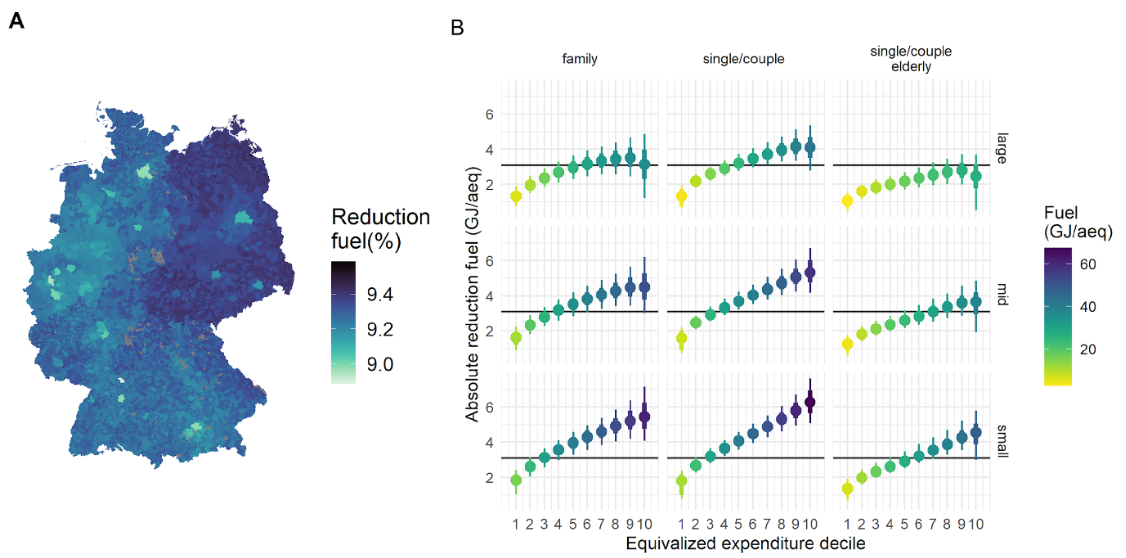

Figure 5. Fuel use response to carbon tax: (A) relative reduction of fuel use, (B) absolute reduction in fuel use per household across expenditure deciles grouped by community size and household type.

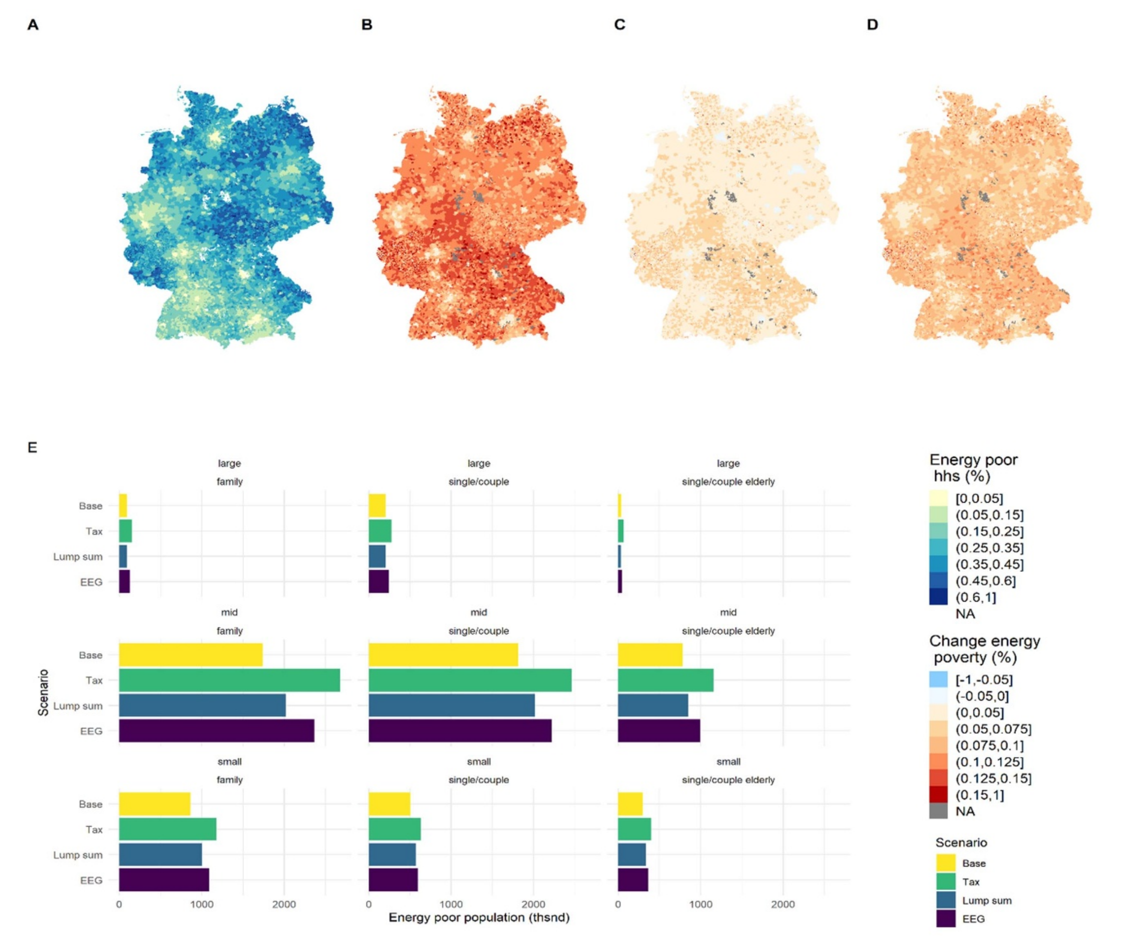

Figure 6. Distribution of impacts on energy poverty: top panel: spatial distribution of the share of energy poor households in the local household population (A), and change of the number of energy poor households (% points) under (B) carbon tax without compensation, (C) lump sum payments, (D) EEG abolishment. Bottom panel: absolute number of energy poor households across the scenarios and across demographics and region size class.

default. The threshold is set at twice the median expenditure for car fuels. This results in an energy poverty threshold of 14.5% of expenditure on heating, electricity and car fuel.

Applying this threshold to our baseline scenario (i.e. the synthetic population) shows that 6.3 million, or 17% of households in Germany are energy poor. Their spatial distribution is concentrated in rural areas that are relatively remote from urban centers and their surroundings, visible as a clear gradient of decreasing energy poverty around urban centers (figure 6(A)). A carbon tax of 50 Euro/tCO_2 without compensation would increase the overall number of energy-poor households to 24%. The highest increase in energy poor households would occur in small rural communities in the south (figure 6(B)), due to their large reliance on oil as their heating source (figure 3(A)) and high car ownership (figure 3(C)). Especially in the areas surrounding large cities, an increase in energy poverty can be observed (figures 6(A) and (B)). In the compensation scenario with a lump sum payment of €100 per capita, the share of energy-poor households is 18.9% (figure 6(C)), which is slightly greater than in the absence of the carbon tax (baseline). In the EEG compensation scenario, it is 21.4% (figure 6(D)). Although the share of energy-poor households increases in both scenarios compared to the no carbon tax baseline, the lump sum payment is much better suited to offset the effects of the carbon tax than the EEG compensation, which would add an additional 1.7 million energy-poor households. In both cases the spatial distribution of energy-poor households remains largely the same as in the baseline.

The tax disproportionately affects families and younger singles and couples, especially in medium sized communities. Energy poverty is least likely to affect households of all types in large cities, and older individuals and couples in all communities. The main reasons for this result are that (1) households in large cities and elderly households use individual motorized transportation less than other household types (Zong *et al* 2022), (2) households in large cities tend to have homes with smaller floor areas, and (3) elderly households are the demographic group with the highest average household income, so they are less likely to spend a significant portion of their income on energy.

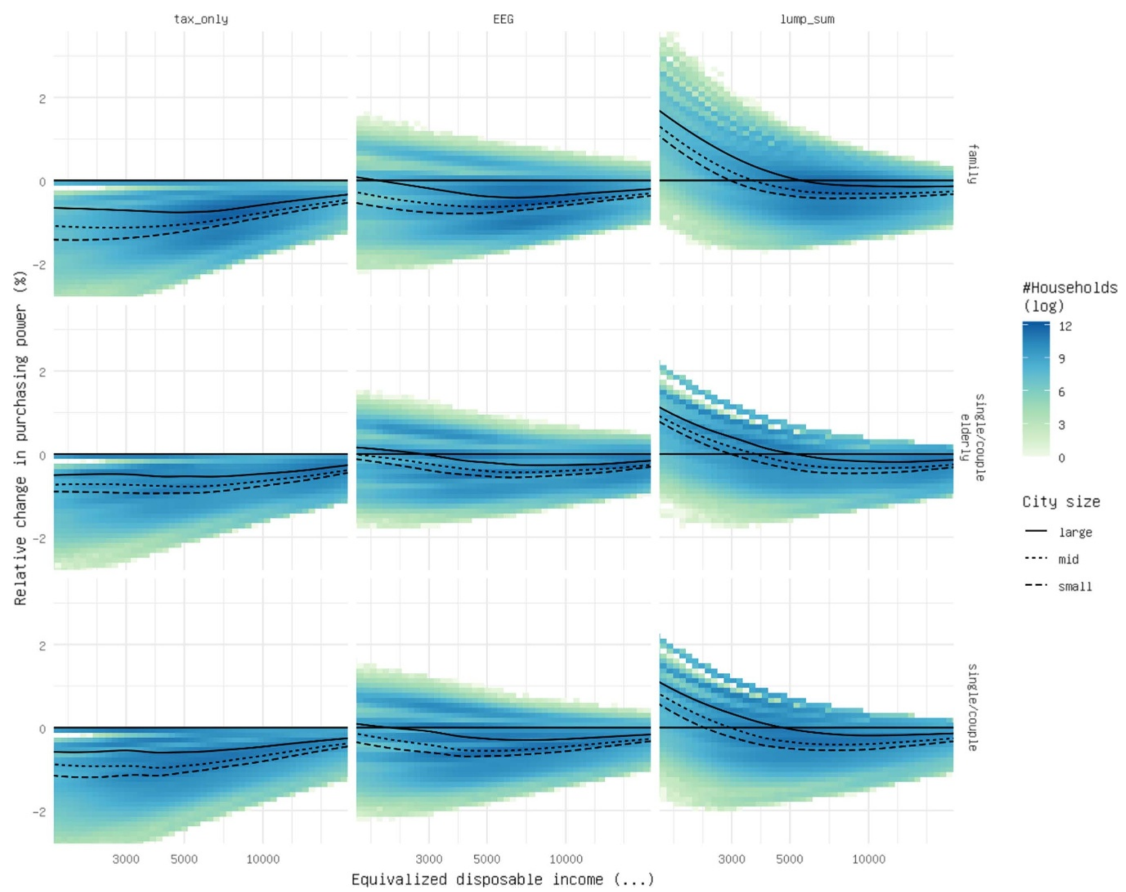

Figure 7. Effects of carbon tax and mitigation schemes on relative change in purchasing power of households by disposable income (€ aeq^{-1}) across community sizes and household types (× cropped to contain 90% of data points).

A major problem with untargeted transfers is that they are expensive, because the funds do not go where they are needed. In this study, for example, we find that the lump sum compensation costs about 8.04 billion Euros. In comparison, the total value of energy expenditures of German households above the energy poverty threshold is about 5.81 billion Euros, or 2.99 billion Euros if only households that can also be considered economically poor (e.g. those in the first four deciles) are included. These figures clearly show that targeted compensation is not only more cost-effective, but also more efficient in fighting energy poverty.

The impact of a carbon tax on household purchasing power varies according to settlement structure, household demographics, and socio-economic factors (figure 7). An unmitigated carbon tax of €50/t has a regressive effect on all household groups meaning that poorer households lose a larger share of their purchasing power than richer households. The magnitude of the purchasing power loss and the strength of the regressivity show a clear urban–rural gradient; both effects are strongest in small communities and weakest in large cities. Families experience larger losses in purchasing power than singles and couples, while older people tend to lose less purchasing power than younger people or families. Families in rural areas are hardest hit, losing up to 1.5% of their purchasing power. The EEG scenario reduces the relative loss of purchasing power for all households and somewhat mitigates the regressive character of the tax. Very poor households (with the exception of families in small and medium-sized cities) have almost no losses under this scenario. However, the tax remains regressive across large parts of the income distribution and the largest losses in purchasing power continue to affect families, especially in rural areas. In contrast, the second mitigation option with the lump sum has a strong progressive effect in the lower-income groups. Households in the lowest income decile, which suffered losses in purchasing power of up to 1.6% in the unmitigated tax scenario, now experience gains in purchasing power of between 1% and 2% across all household types and settlement sizes. Poor families in particular (across all settlement sizes) benefit strongly from receiving the lump sum payment. Overall, there are some purchasing power gains up to the fifth decile, and the purchasing power losses in the upper deciles are relatively small and constant across the top half of the income distribution. In this scenario, the differences between rural and metropolitan communities are also the smallest. The very high variability within income groups, especially in the lower deciles reveals that not all poor households benefit equally from the compensation policies.

4. Discussion and conclusion

At the aggregate level, our results confirm that carbon taxes tend to have a strong regressive effect, in that they hurt the poor more than the rich. For Germany we show that a revenue neutral lump sum transfer, even if untargeted, has the potential to compensate on average for these regressive effects. Compared to that, the abolishment of the EEG levy only slightly reduces the regressive effects of a carbon tax. This corroborates previous findings that compensation policies scaling with household income or expenditure levels, such as cutting taxes on electricity or income, are in general less effective in addressing equity issues than lump sum transfers (Rausch *et al* 2011, Flues F and Thomas 2015, Klenert and Mattauch 2016, Reaños and Wölfing 2018, Cronin *et al* 2019).

Other studies that consider the wider impacts of carbon taxes on the economy, such as on businesses, labor markets and international competitiveness, show that designing optimal carbon taxes is more difficult than the research that focuses solely on households suggests. These studies show that there is an efficiency-equity trade-off (Grainger and Kolstad 2010, Rausch *et al* 2011, Goulder *et al* 2019). On the one hand, compensation via cutting corporate or labor taxes is found to be favorable regarding overall impacts on gross domestic product (GDP), while lump sum transfers, on the other hand, are found to perform best in reducing inequality impacts. The situation is additionally complicated by the fact that the performance of carbon taxes and compensation critically depends on the initial state of the tax system (Jacobs and Mooij 2015; Klenert and Mattauch 2016, Hänsel *et al* 2022).

At the granular level of household types and community sizes, our results show a strikingly consistent pattern. In all four simulations, i.e. baseline, carbon tax without compensation, lump sum transfer and abolishment of the EEG levy, most energy poor households are families and young single/couple households in medium to small communities. These households are many times more likely to experience energy poverty than households in large cities, and the elderly in communities of all sizes.

The spatial distribution of the largest increases in additional energy-poor households reveals that the east and rural areas close to the border in the west and south are most affected by a carbon tax without compensation, and by recycling policies that scale with income or expenditure levels, such as the elimination of the EEG levy. We conclude that, except for large cities, location and household type are more important than the size of the community.

Our results confirm a large degree of heterogeneity of impacts across income groups (vertical inequality). Strikingly though, our results also show that heterogeneity within the same income bracket (horizontal inequality) is even larger. This corroborates the very limited evidence on vertical and horizontal inequality impacts of carbon taxes (Pizer and Sexton 2019, Hänsel *et al* 2022). Specifically, we find that within the same income bracket, the average rural household is affected more than twice as much as the average urban household. This effect is particularly strong among the poorest households and diminishes with increasing income. This effect is largely driven by region-specific factors, particularly the differences between large cities and rural/remote areas in terms of car dependency, heating infrastructure, floor space consumption, and other characteristics of the building stock. These results also reveal another limitation of revenue neutral lump sum transfers; they do not reduce baseline energy poverty. The substantial horizontal variability of purchasing power losses in lower deciles after lump sum compensation implies that many low-income households are still not adequately compensated by lump sum transfers to prevent relative purchasing power losses.

More targeted carbon tax compensation policies face several challenges, some of which can be solved with the presented synthetic population. Importantly, our data set allows us to combine information on households' income and location with information on how much energy they use and for what purposes, a data source that has previously not been available.

An important challenge is that carbon tax compensations should not create a lock-in for inefficient housing and private motorized travel, nor for wasteful energy consumption. The presented synthetic population provides the data to relate households' energy consumption to household size, income, expenditure, location, and to the insulation quality of the dwellings, car dependency and floor space per adult equivalent. This information can be used to derive energy efficiency thresholds for heating and mobility and for necessary vs. luxury consumption.

This information does not directly suggest where the thresholds should be set. The most widely used definition of energy poverty, the relative share of expenditure on energy services, as used in our study, has severe limitations. Many households in the lower income deciles have disproportionally high energy costs due to low quality housing and less efficient cars. At the same time high-income households in rural areas can quickly pass the threshold of energy poverty (e.g. as seen in figure 6(B)) because they inhabit large, detached homes of poor insulation and are highly car dependent. With a high and safe income, passing the energy poverty threshold will not necessarily create existential threats, and a compensation would incentivize the continuation of energy intensive lifestyles. These households are in the position to invest in energy efficiency.

The energy price shocks in many countries caused by Russia's war on Ukraine have heightened the urgency of the challenge of how to incentivize or maintain energy savings or investment in low-carbon technologies, while preventing negative distributional impacts and rising energy poverty. Governments in Germany and other countries have introduced various policies, including lump-sum transfers and energy price subsidies, to relieve households and businesses from ruinous living costs or production costs. Lump-sum transfers to target groups have recently been abandoned in Germany in favor of so-called 'energy price brakes,' as it has become clear that it is not possible to define target groups or reach them with payments without risking that many households in need of assistance will not receive any. However, the 'energy price brake,' which sets a cap on energy prices at 80% of a household's previous year's consumption, has only shifted the problem, as the subsidy also applies to energy-intensive lifestyles of high-income households. This demonstrates that creating equitable burden sharing necessarily requires a decision about what level of energy consumption is appropriate and for whom, which is ultimately a political question.

It can be argued, for instance, that including carbon-centric policies such as carbon taxes into a broader program of social, economic, and democratic reforms would achieve decarbonization more effectively and equitably than relying solely on carbon-centric policies (Green and Healy 2022). In general, the emphasis on economic incentives through policies such as carbon pricing as a means to achieve climate goals is controversial and most popular among growth-centric schools of thought, such as green growth advocates. Others, such as degrowth or postgrowth advocates, emphasize more strongly the need to address inequalities as drivers of the climate crisis, and thus favor policies that reduce inequalities and emissions through major restructuring of economic and social systems, such as coordinated macroeconomic institutions that can finance the universal provision of low-emissions basic services, provide financial security to people, and rule changes that strengthen democratic processes by reducing the concentration of economic and political power. In these Green New Deal-type policy packages, public and democratic institutions play a much larger role in mobilizing the resources necessary for societal transformation than in the purely carbon-centric policies favored by the former ecomodernist camp.

While there may be no consensus on which sets of policies are most efficient at reducing emissions or most socially beneficial, it is probably less controversial that the scale, depth, and speed of the required socio-ecological transformation of industrial societies requires a solid empirical basis for balancing environmental and social goals. We argue that robust evidence-based decision making requires the kind of granular information that our synthetic population dataset provides.

Sufficient access to energy is necessary for private households to meet their basic needs, especially for heating and mobility. This is precisely why energy prices, beyond market mechanisms, are also politically influenced to large extents virtually everywhere (Badcock and Lenzen 2010, Taylor 2020, Metcalf 2021). Even in rich countries such as Germany, there are a large number of households for which rising energy prices have a major impact on disposable income, thereby threatening their livelihoods (Speck 1999, Flues and Thomas 2015, Pizer and Sexton 2019, Ohlendorf *et al* 2021). Policymakers therefore need to respond to rising energy costs, whether the price increase is intentional, as in the case of a carbon tax for climate change mitigation (Nordhaus 2007, Klenert *et al* 2018), or whether it is due to geopolitical conflict or supply chain disruption, as in the context of Russia's war against Ukraine or China's closure of ports as part of its COVID response (IMF 2020).

The German federal government put into force a new ambitious climate protection law in December 2019. Similar laws have been passed in other jurisdictions or are being developed. At least since Emmanuel Macron's failed attempt to introduce a fuel tax without considering which households in which regions will be impacted, and to what extent, politicians should be aware of the spatial and socio-economic determinants of the policy impacts they create. Our method to combine population, household and building census counts using rich household microdata on the relationships between demographics, socio-economics, living conditions, income, energy expenditure, community size and geographical locality is replicable to any jurisdiction for which similar underlying data are available. For such jurisdictions, our method allows the assessment of the impact of any energy price shock and compensation legislation. Our results also point to the limits of what individual households can do themselves, and highlight regional and socio-economic hotspots, where not only compensation, but also investment from state or national funds is essential for sufficient voter support for successful climate mitigation measures.

Data availability statement

Access to the household microdata is granted for research purposes by the Federal Statistical Office (www.forschungsdatenzentrum.de/de/haushalte/evs). Census data are available at www.zensus2011.de/DE/Home/Aktuelles/DemografischeGrunddaten.html. Data on primary and disposable income at county level is available at www.statistikportal.de/de/vgrdl/ergebnisse-kreisebene/einkommen-kreise. Data on heating energy and electricity consumption are available at https://ag-energiebilanzen.de/wp-content/uploads/2020/10/ageb_20v_v1.pdf and data on household's consumption of transportation fuels are available at www.bmvi.de/SharedDocs/DE/Publikationen/G/verkehr-in-zahlen-2021-2022-pdf.pdf?__blob=publicationFile. Data on consumer prices are available at www-genesis.destatis.de/genesis/online. Concordance tables, the synthetic population and simulation results are available at https://gitlab.pik-potsdam.de/toebben/bymarka.ctpaper.

The data that support the findings of this study are openly available at the following URL/DOI: https://gitlab.pik-potsdam.de/toebben/bymarka.ctpaper.

Code availability

R code for the generation of the synthetic population, the simulation of carbon taxes as well as for generating the figures shown in the paper and the supplementary information are available at https://gitlab.pik-potsdam.de/toebben/bymarka.ctpaper.

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