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The heterogeneous effects of climate policy on households: Evidence from 88 countries[☆]

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ABSTRACT

We analyze the distributional effects of climate policy by examining heterogeneity in households' carbon intensity of consumption. We construct a novel dataset that includes information on the carbon intensity of 1.7 million individual households from 88 countries. First, we show that horizontal differences are generally larger than vertical differences. Then, we use supervised machine learning to analyze the non-linear contribution of household characteristics to the prediction of carbon intensity of consumption. Household income, proxied by total household expenditures, is usually an insufficient predictor for the additional costs of climate policy. Including household-level information beyond household income increases the accuracy of prediction. Our results highlight that, depending on the context, some compensation policies may be more effective in reducing overall heterogeneity than others.

1. Introduction

The second theorem of welfare economics posits that matters of efficiency and equity are perfectly separable. With application to climate change mitigation, carbon pricing would equalize marginal abatement costs across emitters, inducing emission reductions at lowest aggregate costs. Complementing transfers – possibly financed through carbon pricing revenues – would then offset resulting price increases for goods and services, alleviating potentially unintended distributional consequences.

For a long time, this basic tenet of economic theory has guided our thinking about the distributional effects of climate policy. In practice, however, governments face important information constraints. Ex ante, it is often unclear how the costs of climate policy will be distributed across households, whether the use of existing compensation policies will be sufficient to address these costs, and what new instruments would be needed to achieve any distribution of costs that is politically desirable. In particular, large horizontal heterogeneity (Fischer and Pizer, 2019; Hänsel et al., 2022), that is, differences in additional costs within income groups, can reduce the effectiveness of uniform lump-sum transfers, which are often proposed for their administrative simplicity and

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progressive effects. Designing effective compensation policies, i.e., minimizing targeting errors, is thus important to advance public support for climate policy (Maestre-Andrés et al., 2019; Dechezleprêtre et al., 2025) and to ease fiscal pressure. Yet, our understanding of which compensation policies would be effective in achieving which distribution of costs *post*-compensation is crude.

In this study, we address this gap by analyzing the heterogeneous household-level impacts of climate policy instruments in 88 countries, comprising more than five billion people. Our main variable of interest is the carbon intensity of consumption, representing the short-term relative additional costs of any policy that increases the marginal cost of emitting CO_2. We go beyond traditional analyses of vertical and horizontal heterogeneity of policy impacts and use supervised machine learning to disentangle the non-linear contributions of household characteristics to the *overall* variation in the carbon intensity of consumption.

We show that across the entire sample, horizontal differences in carbon intensity exceed vertical differences. Heterogeneity in income, proxied by total household expenditures, is often insufficient by itself to predict the additional cost burden from climate policy. Including other household characteristics beyond household expenditures, e.g., vehicle ownership, information on household location, and energy use, substantially improves prediction accuracy. Our results point to country- and policy-specific distributional impacts that call for compensation policies tailored to each country context.

We make three important contributions to analyses of distributional effects of climate policy and their potential alleviation: First, we compile a novel and harmonized dataset on the carbon intensity of consumption, covering 1.7 million individual households in 88 countries. In contrast, previous work has often focused on single-country contexts or neglected within-country characteristics at the household level. Second, we make use of different approaches to systematically describe and visualize overall, vertical and horizontal heterogeneity, consolidating and extending existing methods. Third, we apply supervised machine learning to capture non-linear relationships between household characteristics and carbon intensity of consumption, extending a nascent literature that focuses primarily on linear models. We thus contribute to a more systematic understanding of country-specific characteristics of distributional impacts with important implications for the design of complementing compensation policies.

We proceed as follows: In Section 2, we motivate our work with a theoretical framework describing the distributional impacts of climate policy and their relevance for governments in designing complementary compensation policies. In Section 3, we describe our modeling approach and analytical methods. In Section 4, we analyze the heterogeneous effects of climate policy both between and within income groups and present the relative importance of household characteristics for predicting carbon intensity at the country level. Finally, we discuss our findings in light of ongoing debates about how to avoid or address unintended distributional impacts of climate policy in Section 5 before concluding in Section 6.

2. Theoretical framework: Distributional impacts of climate policy

We present a theoretical framework that incorporates the decision problem of a government faced with heterogeneous impacts of climate policy across households. We integrate several aspects from research on the distributional implications of climate policy to motivate our core research questions. Similar approaches in political economy research describe the role of heterogeneous interest groups for governments to enact climate policies (Fredriksson, 1997; Aidt, 1998). In addition, we consider the ability of governments to ease additional costs and their unequal distribution through compensation policies (Lindbeck and Weibull, 1987; Cremer et al., 2004; Aidt, 2010). In contrast to such approaches, which consider governments to maximize aggregate welfare, vote shares, or contributions by interest groups, we assume that governments maximize public acceptance (e.g., Downs, 1957; Stigler, 1971) when faced with the choice of climate and compensation policies.

Choice of climate policy. We consider the government of any country r with an exogenous target to reduce CO_2 emissions.[1] Governments can achieve their target by introducing one or more novel climate policy instruments $p \in P$. Such instruments can differ in many dimensions, including cost-efficiency, transaction costs, or institutional requirements, but here we focus on household (or voter) acceptance as the relevant criterion for influencing governments' choice of a policy or combination of policies.

The introduction of climate policy p leads to additional costs $c_{i,p} \geq 0$ in household *i*. This proposition is reasonable for demand-side policies, but also for supply-side policies, assuming that firms pass on additional costs to households.[2] We therefore neglect the distribution of costs across regulated industries. We also focus on changes in consumption costs, neglecting effects of climate policy on wages or capital income. Variable $c_{i,p}$ refers to the *relative* additional costs (in % of household income), reflecting the diminishing marginal utility of income.

The relative additional costs c_p differ for different households, where $\psi(c_p)$ represents heterogeneity in household-level costs. Differences in c_p express both household-level differences in income and access to (and use of) less polluting technologies (Hänsel et al., 2022): Relative additional costs are higher for lower-income households with equal access to less polluting technologies and for households with equal levels of income that use more of the regulated polluting technology. More specifically, relative additional costs reflect expenditure shares for polluting goods, which differ with income (Jacobs and van der Ploeg, 2019; Dorband et al., 2019). Both household income and the use of less polluting technologies are part of a set of household characteristics X_i.

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[1] This implies that we ignore government preferences for more or less stringent climate policy, as well as the benefits of abated climate change and their distribution across households.

[2] Manufacturing pass-through rates for changes in energy prices are likely to differ from unity and both between and within industries (Sharat et al., 2020; Cludius et al., 2020). In general equilibrium, such pass-through rates depend inter alia on plant-specific technology use, available substitution technologies, within-industry competition, and demand elasticities. In the short-term, adjustments in production technologies may be challenging, such that increases in energy prices can be considered increases in marginal production costs.

Governments thus choose a set of climate policy instruments P^* that lead to household-specific costs c_{i,P^*} and resulting heterogeneity $\psi(c_{P^*})$ determined by household heterogeneity in income and technology use.

Choice of compensation policy. In addition, governments can introduce one or more compensation policies $t \in T$, which is a frequently proposed option to address unintended costs of climate policy (Baranzini et al., 2017; Klenert et al., 2018). Such compensation policies include household-level benefits $b_{i,t} \geq 0$ (in % of household income) that depend on household characteristics X' (e.g., Akerlof, 1978). For example, one option is to reduce income taxes, which has its merits on efficiency grounds (Pearce, 1991; Goulder, 1995; Bento et al., 2018). In our framework, this would lead to compensation benefits $b_{i,t}$ differentiated by income in household i. Importantly, governments can only observe a subset X' of household characteristics X, and compensation policies are only available for such observable characteristics.[3]

Compensation policies that are targeted based on household characteristics pose a challenge for governments to ensure that transfers reach households eligible for compensation (e.g., Hanna and Olken, 2018). Research addressing the design of transfers in the absence of information on recipients confirms that such *targeting errors* can be substantial, especially in non-industrialized countries (World Bank, 2018; Robles et al., 2019; Bah et al., 2019) due to limited institutional capacity (e.g., Besley and Persson, 2009) and higher administrative costs (Coady et al., 2004) required to improve precision.

One alternative is a compensation option that is not conditional on household characteristics X', e.g., a uniform lump-sum transfer. Indeed, a uniform lump-sum transfer is a popular recommendation in the case of climate policy (Stiglitz et al., 2017; Baranzini et al., 2000; Metcalf, 2009; Sager, 2023), precisely because governments require little information about the recipients and because such transfers ease the costs for poorer households (Budolfson et al., 2021; van der Ploeg et al., 2022).

If such transfers were not available, governments could resort to other theoretically conceivable compensation policies that are not conditional on household characteristics, such as financing public infrastructure (Jakob et al., 2016; Franks et al., 2018), subsidizing or providing subsistence goods (Schaffitzel et al., 2019; Greve and Lay, 2022), or green spending (Kotchen et al., 2017; Sommer et al., 2022; Dechezleprêtre et al., 2025). We denote benefits from transfers that are not conditional on household characteristics by $b_{i,\varepsilon}$.

We assume that governments finance compensation policies through an exogenously given budget. Thus, we neglect administrative costs of implementing each climate or compensation policy, application costs at the household level, and strict budget constraints.[4]

The naïve incidence on households. The difference between the costs of climate policy and the benefits of compensation policy leads to a naïve incidence π_i in household i, where

$$\pi_i = \underbrace{-\sum_{p\in P^*} c_{i,p}}_{\text{costs from climate policy } (\leq 0)} + \underbrace{\sum_{t\in T}(b_{i,t} + b_{i,\varepsilon})}_{\text{benefits from compensation policy } (\geq 0)} \tag{1}$$

This household-specific incidence π_i, i.e., the net relative budget change, can be positive or negative, and depends on the governments' choice of climate and compensation policy instruments. The heterogeneity in such incidence across households thus depends on the prevailing heterogeneity in additional costs $\psi(c_{P^*})$ and on the choice of transfers by governments. The minimum heterogeneity that governments can achieve is limited by whether the sum of additional costs c_{P^*} is correlated with observable household characteristics X^*. This correlation affects whether compensation can help reduce heterogeneity across households. Nevertheless, we assume that household characteristics X' are exogenous: Households cannot change their household characteristics in the short term, e.g., by improving home insulation or reducing demand for emission-intensive modes of transport.[5] This implies that expectations about the short-term incidence of households π_i cannot influence household characteristics X_i.

Distributional effects of climate policy. An important determinant for public acceptance is equity. Our *naïve* expression of households' incidence captures the short-term net budget change, but does not take into account whether households perceive this incidence to be acceptable *in comparison* to other households. We therefore introduce two additive terms in our framework that account for households' perceptions of distributional effects. Specifically, we propose to decompose overall heterogeneity into heterogeneity between income groups and heterogeneity within income groups, or, more specifically, heterogeneity that cannot be explained by heterogeneity in income.

We start with *vertical* distributional effects, which describe differences in additional costs between income groups. Let q refer to income groups and V_i to the importance of vertical differences for household i, expressed in monetary terms:

$$V_i = \sum_{q_j} \delta^V_{i,q_j} * (\overline{\pi_{q_i}} - \overline{\pi_{q_j}}) \text{ with } q_i \neq q_j \tag{2}$$

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[3] For example, governments can compensate households by lowering taxes on vehicle ownership or transport fuel consumption, which are observable. They may not compensate households by linking benefits to environmental attitudes or the use of efficient appliances, which are difficult to observe.

[4] Nevertheless, this framework could in principle be used to calculate how much budget should be spent to increase targeting precision, assuming that heterogeneity in the costs of climate policy should be reduced to a minimum. Including a strict budget constraint may also serve the purpose of testing the potential of revenue-generating, but *revenue-neutral* climate policy instruments (such as carbon pricing or fossil fuel subsidy reforms with revenue recycling) to reduce additional costs to households.

[5] Available technologies and infrastructure determine the substitution elasticities of households, which, in turn, are a critical determinant of costs to households in the medium-term.

$\overline{\pi_{q_i}}$ denotes the median additional costs in income group q_i. Variable δ^V_{i,q_j} expresses the sensitivity of household i to vertical differences between its income group q_i and other income groups q_j. For example, it is reasonable to assume that households are interested in comparing the median additional costs of relatively poorer or richer households, i.e., whether a policy would lead to progressive or regressive outcomes (e.g., Dechezleprêtre et al., 2025). δ^V_{i,q_j} can be thought of as a measure of inequality aversion at the household level, indicating how much money each household would be willing to spend to reduce vertical heterogeneity.

It is popular to analyze the distributional effects of climate policy instruments with a focus on vertical heterogeneity, i.e., heterogeneity in policy outcomes between relatively poorer and relatively richer households.[6] For price-based climate policy instruments (such as carbon pricing), such work includes analyses in single countries (Poterba, 1991; Grainger and Kolstad, 2010; Rausch et al., 2011; Goulder et al., 2019; Garaffa et al., 2021; Sterner, 2012; Wu et al., 2022) or across countries (Dorband et al., 2019; Vogt-Schilb et al., 2019; Budolfson et al., 2021; Feindt et al., 2021; Steckel et al., 2021; Missbach et al., 2024). Price-based policies covering all sectors are often found to be regressive, especially in high-income countries.[7] In contrast, a meta-analysis (Ohlendorf et al., 2021) documents more progressive results in lower-income countries and for price-based policies in the transport sector.

A second important dimension is *horizontal* distributional effects, i.e., differences in additional costs among similarly poor or similarly rich households (Rausch et al., 2011; Fischer and Pizer, 2019). Let H_i denote the importance of horizontal differences for household i, expressed in monetary terms:

$$H_i = \sum_q \delta^H_{i,q} * H_q \tag{3}$$

H_q denotes differences in additional costs within income groups. One measure of H_q can be the difference between the 5th and 95th percentiles in each income group, i.e., $H_q = \pi^{95}_q - \pi^5_q$. Variable $\delta^H_{i,q}$ expresses the sensitivity of household i to horizontal differences within income groups. This measure also reflects the relative position of household i in its income group q_i, e.g., $\frac{\pi_{i,q}}{\overline{\pi_q}}$. In general and depending on the definition of income group, horizontal heterogeneity comprises all heterogeneity that cannot be attributed to income heterogeneity. Similarly to δ^V_{i,q_j}, variable $\delta^H_{i,q}$ can be thought of as a measure of inequality aversion at the household level, indicating how much money each household would be willing to spend to reduce horizontal heterogeneity.

Researchers have begun to take an interest in the horizontal distributional effects of climate policy, partly as a result of the empirical observation that variation *within* income groups can differ more strongly than *between* them (Cronin et al., 2019; Pizer and Sexton, 2019; Steckel et al., 2021). Such horizontal differences indicate that households use technologies with heterogeneous carbon intensity, but such differences in available technologies cannot be attributed to heterogeneous levels of household wealth (Hänsel et al., 2022). The analysis of the determinants of horizontal distributional effects is receiving increasing attention: Research highlights the role of energy use patterns (Steckel et al., 2021; Missbach et al., 2024), differences in the spatial dimension (Chan and Sayre, 2023; Burtraw et al., 2009), and sociodemographic variables (such as household size, education, ethnicity, and occupation (Grainger and Kolstad, 2010; Büchs and Schnepf, 2013; Farrell, 2017; Fremstad and Paul, 2019; Missbach et al., 2023)) for horizontal heterogeneity, but compared to research on the drivers of vertical distributional effects, such analyses remain scarce.

Horizontal distributional effects are particularly important for the design of compensation policies. For example, combining price-based climate policies with revenue-neutral and uniform lump-sum transfers would lead to a more progressive distribution of additional costs, but would neglect or even increase horizontal differences within income groups (Cronin et al., 2019; Hänsel et al., 2022). This is because such undifferentiated transfers would not compensate those households that bear the highest additional costs (Fullerton and Muehlegger, 2019; Sallee, 2019; Missbach et al., 2024). Instead, reducing horizontal heterogeneity may justify differentiated transfers.

The government decision problem. Our theoretical framework features the static decision of governments to choose a set of climate and compensation policies that maximize public acceptance. Maintaining public acceptance or support can be seen as a core objective of governments, and research suggests that lack of public acceptance has been detrimental to effective climate policy implementation (Carattini et al., 2018; Bergquist et al., 2022; Douenne and Fabre, 2022).

We assume that governments are primarily concerned with the short-term effects of policies and public acceptance. We ignore the intertemporal dimension and neglect the dynamic responses of households to climate and compensation policies, which may alter the additional costs and their distribution. We express the government decision problem as follows:

$$\max_{P^*,T} \Theta = \sum_i \mu_i * \rho_i(\pi_i + V_i + H_i) \tag{4}$$

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[6] Our study is also related to research that compares within-country heterogeneity in carbon-intensive consumption across countries and time. For example, Chancel (2022) creates a time series of carbon footprints at the level of countries and percentiles to study *carbon inequality* within countries. Others (Yannick et al., 2020; Bruckner et al., 2022) compare the distribution of carbon footprints across and within countries, but such macro-level studies tend to be silent on policy impacts and their associated vertical and horizontal distributional implications.

[7] Another strand of research explores vertical distributional impacts for other climate policy instruments, such as fossil fuel subsidy removal (Schaffitzel et al., 2019; Giuliano et al., 2020; Granado et al., 2012), technology standards (Levinson, 2019; Bruegge et al., 2019; Zhao and Mattauch, 2022), subsidies for cleaner goods (Borenstein and Davis, 2016; Vaishnav et al., 2017; Winter and Schlesewsky, 2019), and behavioral interventions (DellaValle and Sareen, 2020; Liebe et al., 2021). Essentially, all policy instruments are found to have some vertical distributional effects, reflecting heterogeneous preferences for and endowments with less polluting technologies across different income groups.

The term $(\pi_i + V_i + H_i)$[8] expresses the cost of a set of climate and compensation policies P^* and T for household i, including the naïve incidence and households' aversion to vertical or horizontal distributional effects. Such costs are the argument to function $\rho_i(\bullet)$ that reflects each household's loss aversion (Tversky and Kahneman, 1991) and helps translate monetary costs into a measure of acceptance.[9] μ_i denotes weights of the government for each household's acceptance to reflect that governments may seek higher acceptance from certain interest groups than from others.

It is important to note that μ_i is a normative term that expresses governments' preferences for accepting or declining a particular distribution of the costs of climate policy. For example, it could reflect that governments prefer climate policy instruments with the least distributive distortions (Fischer and Pizer, 2019). By comparison, variables δ^V_{i,q_j}, $\delta^H_{i,q}$, and function $\rho_i(\bullet)$ are positive household-level terms that describe households' perceptions of fairness and their willingness to accept climate policy costs. We treat such terms as exogenous, leaving them to various strands of research on household-level loss aversion and perceptions of fairness.

In essence, governments face a trade-off between efficiency and equity (Dinan et al., 2016; Hänsel et al., 2022; Drupp et al., 2024) because some households have access to less carbon-intensive technologies while others do not, implying that efficiency-enhancing climate policies may lead to increased inequality. Eq. (4) shows that maximizing public acceptance of climate policy requires easing additional costs to households and their unequal distribution. Governments have the option of choosing complementary compensation policies, and Eq. (1) shows that effective design of such compensation policies requires precise information about household-level characteristics that help explain differences in additional costs.

Following our theoretical framework, we contribute to a better understanding of the distributional impacts of climate policy and the requirements for effective compensation policies. First, we analyze the distribution of the costs of climate policy instruments, i.e., we are interested in $\psi(c_p)$. The distribution of such costs depends on the distribution of income and less polluting technologies, which leads us to analyze $\psi(c_p)$ at the country level and for a wide range of countries and policy instruments with different regional or sectoral coverage. Second, we analyze the contribution of heterogeneity between income groups to overall heterogeneity, in conjunction with systematically describing the vertical and horizontal distributional effects of climate policy, i.e., comparing additional costs across and within income groups. Third, we ask: Which household characteristics X' can help explain the variation in additional costs c_p? This can contribute to help solving the government decision problem by reducing vertical and, in particular, horizontal distributional effects. Understanding which households are affected may have implications for climate and compensation policies across countries if different household characteristics are associated with variation in the additional costs of climate policy.

3. Data and methods

We derive the heterogeneous costs of climate policy on households by analyzing the heterogeneity in the carbon intensity of consumption: Assume that the consumption of household A is twice as carbon-intensive as the consumption of household B, then climate policy will lead to twice as high costs for household A compared to household B and relative to total expenditures.[10]

In this section, we first describe the construction of a novel dataset that captures household-level carbon intensities across countries.[11] We then describe how to explore and compare the vertical and horizontal heterogeneity in carbon intensities. We also present our approach to analyzing such heterogeneity with supervised machine learning, which helps unravel the contribution of individual household characteristics to predicting households' carbon intensities.

3.1. Household-level carbon intensities: A novel dataset

The carbon intensity of consumption of household i, denoted by e_i, is the variable of interest in this study. It reflects both direct and indirect[12] CO_2 emissions E_i in household i relative to total consumption Y_i and thus the additional cost of climate policy at the household level $c_{i,p}$, as described in Section 2. We express e_i in $\frac{kgCO_2}{USD}$. More specifically, the carbon intensity of consumption represents the carbon intensities of different sectors e_s, weighted by the expenditure shares in household i for goods and services from each sector s, denoted as $w_{i,s}$:

$$e_i = \frac{E_i}{Y_i} = \frac{\sum_s e_s * Y_{i,s}}{\sum_s Y_{i,s}} = \sum_s e_s * w_{i,s} \tag{5}$$

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[8] Additivity is a reasonable assumption because each term refers to an independent source of costs.

[9] It is reasonable to assume that $\rho_i'(\bullet) < 0$, i.e., that household acceptance is decreasing with increasing monetary costs including costs that households would be willing to spend in order to reduce vertical and horizontal distributional effects.

[10] This proposition holds under the assumption that climate policy raises supply-side input prices in line with the *embedded* CO_2 emissions associated with production, and that firms cannot respond to changing input prices in the short term. As a corollary, output prices for consumer goods and services would increase in proportion to embedded (direct and indirect) CO_2 emissions. More generally, the carbon intensity reflects the additional cost of any policy that increases consumer prices in proportion to embedded CO_2 emissions, independent of existing policies, but also independent of regulation stringency. One visible example of the equivalence of e_i and c_{i,P^*} is an upstream carbon tax, as we demonstrate in Appendix A.5.

[11] Supplementary Figure A.1 visualizes key elements of our data work and analyses.

[12] Direct CO_2 emissions refer to emissions resulting from the combustion of fuels in households, e.g., for transportation or heating. Indirect CO_2 emissions refer to emissions that can be attributed to the production, transportation, and retail of all goods and services purchased by each household, such as emissions from electricity generation or manufacturing processes.

In addition, it is possible to examine the carbon intensity at the household level for different sectors s, denoted by $e_{i,s}$, which allows for understanding the heterogeneous impacts of different policies p with different sectoral or regional coverage, such as policies targeting the transport or electricity sectors, or trade policies such as carbon border adjustments.

Sectoral expenditure shares. We collect information on sectoral expenditure shares at the household level $\left(w_{i,s} = \frac{Y_{i,s}}{\sum_s Y_{i,s}}\right)$ from household budget surveys (see Table A.1 for an overview). In such surveys, households report their expenditure on goods and services at the item level, from which we compute sectoral expenditure shares.[13] We include survey datasets in our study if they cover a nationally representative sample, include item-level expenditure information, and if the surveys were conducted between 2010 and 2019.[14] After several cleaning steps,[15] our resulting dataset contains information on more than 1.7 million individual households representative of the populations of 88 countries that account for more than 5 billion people, 68% of global GDP, and 51% of global CO_2 emissions.[16]

We include total household expenditures as a surrogate for household income in our dataset because total household expenditures are a better proxy for *lifetime* income (Poterba, 1989, 1991; Cronin et al., 2019) and because wage data from such surveys are often unreliable (Blundell and Preston, 1998). In the remainder of the study, we consider total household expenditures and income as synonyms.[17]

In addition, our dataset includes sociodemographic information on household members (such as education, gender, nationality, main language, self-identified ethnicity, or religion of household representatives), detailed spatial information (such as province, district, or village of households), and information on energy use (such as the main fuels used for cooking, lighting, and heating) or appliance and vehicle ownership. Such household-level information (including total household expenditures) forms the set of variables X_i', which allows the analysis of differences between households with different characteristics.[18]

Sectoral carbon intensities. We complement expenditure share data with country- and sector-level carbon intensities $e_{s,r}$, which represent the (fossil) CO_2 emissions that can be directly or indirectly attributed to a unit of (household) consumption (in USD) from sector s in region r:

$$e_{s,r} = \frac{E_{s,r}^{direct} + E_{s,r}^{indirect}}{\sum_i Y_{i,s,r}} \tag{6}$$

We derive total sectoral consumption ($\sum_i Y_{i,s,r}$), direct ($E_{s,r}^{direct}$) and indirect ($E_{s,r}^{indirect}$) CO_2 emissions from multi-regional input–output (MRIO) data. This approach is popular among researchers because it accounts for inter-national and inter-sectional differences in production processes and trade flows, while providing sufficient detail for high sectoral resolution. As a result, $e_{s,r}$ expresses CO_2 associated with final household demand for each sector and country, accounting for all fossil CO_2 emissions that occur along the entire value chain.

We capitalize on trade data from the GTAP database (Version 11C, Aguiar et al., 2022), which we transform into MRIO data (Peters et al., 2011), reflecting input–output relationships between 65 sectors s in 160 countries r. We then compute the *Leontief*-inverse $L_{r',s'}^{r,s}$, which captures information about the inputs required by each sector s' and region r' to produce one unit of output in each sector s and region r. We derive the indirect CO_2 emissions $E_s^{indirect}$ as follows:[19]

$$E_s^{indirect} = \sum_{r'} \sum_{s'} e_{r',s'} L_{r',s'}^{r,s} Y_s \tag{7}$$

In addition, the GTAP database also includes information on direct CO_2 emissions E_s^{direct}. This covers CO_2 emissions resulting from the household-level use of fossil fuels, such as gasoline, natural gas, LPG, and hard coal, but not from biomass including charcoal.

Our result is a matrix containing information on the (fossil) carbon intensities of (household) consumption $e_{s,r}$ for 65 sectors s and 160 countries r. These data reflect differences in technologies, prices, and trade relations between sectors and countries for the year 2017. We show all country- and sector-level carbon intensities used in this study in Supplementary Figure A.3.

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[13] We match consumption items to sectors using matching tables. We share all matching tables through a stable online data repository. See Appendix D.2. Figure A.2 shows country-level Engel curves for energy, goods, services, and food.

[14] We exclude more recent survey data, where available, to account for potential biases induced by large economic shocks, such as those associated with Covid-19.

[15] Appendices A.1 and A.2 list details on cleaning and on our efforts to harmonize household characteristics across countries.

[16] We calculate these figures using data for population, GDP, and CO_2 emissions from the World Development Indicators Database (World Bank, 2023) for 2019.

[17] Nevertheless, we acknowledge the documented differences between using expenditure or income data to calculate carbon footprints (see Lévay et al., 2023).

[18] Table A.2 shows summary statistics for all countries in our sample; Table A.3 shows average household expenditures and average energy expenditure shares for each expenditure quintile and each country. We also show the proportions of households that use different cooking fuels (Table A.4) and lighting fuels (Table A.5), and that own various major appliances (Table A.6) for all countries for which such data are available.

[19] See Vogt-Schilb et al. (2019); Steckel et al. (2021); Feindt et al. (2021); Missbach et al. (2024) for a detailed description of this approach. The simulation of different sectoral and regional policies is possible by excluding different sectors s or countries r.

Our flexible framework also allows us to analyze the impact of policies targeting non-CO_2 emissions, such as CH_4, N_2O, and F-gases. In our main analysis, we focus on national carbon intensities, i.e., how much CO_2 emissions resulting from production in each country can be attributed to a unit of output. This would be equivalent to zero carbon intensities for imported products, but reimported emissions would be included. See also Appendix A.5.

A novel cross-country dataset. Our resulting dataset integrates information on household characteristics and household expenditure shares with country- and sector-level carbon intensities, as described in Eq. (5). Specifically, it consists of nationally representative accounts of the carbon intensity of household consumption e_i.[20] Capturing detailed information on multiple household characteristics allows us to analyze heterogeneity in carbon intensity. To our knowledge, such a dataset linking household-level information to sectoral expenditure shares, weighted by country- and sector-level carbon intensities, is unprecedented and may help to inform more detailed policy analysis in the future.[21]

3.2. *Descriptive analysis: Heterogeneity in carbon intensity*

We proceed with a descriptive analysis of the heterogeneity in carbon intensity of consumption to motivate our focus on the vertical and horizontal distributional impacts of climate policy at the country level.

Across all countries, the average carbon intensity of household consumption is 0.53 kgCO_2/USD.[22] The average carbon intensity is highest for South Africa (2.02 kgCO_2/USD) and lowest for Malawi (0.03 kgCO_2/USD).[23,24]

Depending on each country, different sectors are more important in driving the carbon intensity of consumption. Table A.8 shows country-level averages and standard deviations for shares of carbon intensities by consumption category. Across countries, expenditures on services are the most important component of household carbon intensities (23%), followed by expenditures on transport fuels (22%) and cooking fuels and other residential energy (21%). Differences between countries in consumption category shares either reflect country-level differences in expenditure shares on different categories or differing sectoral carbon intensities of production.

Analyses of the distributional impacts of climate policy often focus on comparing the average (or median) costs of policies for different income groups of households. A common approach is to assign households to income (or expenditure) quintiles to infer about vertical heterogeneity. More recently, researchers have also begun to compute measures of within-group heterogeneity, such as the 25th or 75th percentile within each expenditure quintile (Cronin et al., 2019; Missbach et al., 2024). Comparing such percentile costs across expenditure quintiles can help to infer about horizontal heterogeneity.

We are interested in overall heterogeneity and to what extent variation in income can help explain such heterogeneity. The Theil index is a measure of *overall* heterogeneity and can be additively decomposed into two components describing variation between and within groups, respectively (Shorrocks, 1980; Cowell, 2011). Fig. 1 visualizes the Theil index for the carbon intensity of consumption in all countries of our sample. Bars show the share of variation between and within expenditure quintiles, respectively, that sum up to overall heterogeneity.

Fig. 1 shows that within-quintile heterogeneity (95% on average) far exceeds between-quintile heterogeneity (5% on average) in all countries. This result is robust to various sensitivity analyses including an analysis with expenditure deciles or expenditure percentiles (see Table A.9). This highlights the fact that analyses relying on differences in income to explain differences in the carbon intensity of consumption may be inadequate because they fail to account for differences in carbon intensity at similar income levels. Instead, we suggest including household-level characteristics beyond income in such analyses to provide a more nuanced description of which households' consumption is particularly carbon-intensive.

This step is warranted also because within-quintile heterogeneity may *vary* across quintiles, as we show in Figure A.4, which visualizes the distribution of carbon intensities for all expenditure quintiles across all countries. For the descriptive purpose of facilitating the comparison of vertical and horizontal differences across countries, we abstract from comparisons between all income groups (as in Eqs. (2) and (3)) and introduce two coefficients (Missbach et al., 2024):[25] The *vertical distribution coefficient* $\widehat{V}_r$ compares the median carbon intensity of the poorest (*q1*) and richest expenditure quintiles (*q5*):

$$\widehat{V}_r = \frac{\overline{e_{q1}}}{\overline{e_{q5}}} \tag{8}$$

If the median carbon intensity of poorer households exceeds (is less than) the median carbon intensity of richer households, then $\widehat{V}_r > 1$ ($\widehat{V}_r < 1$) and climate policy would likely lead to regressive (progressive) outcomes.

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[20] The carbon intensity of household consumption expresses household use of technology and preferences for energy services through sectoral expenditure shares. Everything else being equal, switching to cleaner technologies would lead to a lower carbon intensity as household expenditures on fuels would decline. Reducing energy consumption through behavioral change would also result in lower expenditures on fuels, thus lower expenditure shares on fuels and thus a lower carbon intensity of consumption. Thus, without observing household technology and habits, e_i represents the relative additional costs of climate policy (see also Appendix A.5), and, most importantly, variation in such costs.

[21] See Appendices D.1 for more information about data availability and D.2 for information about code written for cleaning, modeling, and analysis.

[22] It is important to note that our measure of carbon intensity of household consumption can differ from other carbon intensity measures in the literature, e.g., the average CO_2 emissions per GDP. We base our analysis on household expenditure data and household expenditures can be substantially smaller than income, which leads to an increase in the carbon intensity of consumption. Nevertheless, our main analysis focuses on the heterogeneity of households' carbon intensity, which requires that household expenditure data express differences in expenditure shares at the household level and that MRIO data express differences in carbon intensities at the sector level.

[23] See Table A.7 for average carbon intensities for all countries.

[24] Country-level CO_2 intensities help to infer about the relative average costs of climate policy across countries: For example, a carbon price of USD 40 per tCO_2 (Stiglitz et al., 2017) would be equivalent to an average relative cost of 2.12% of total annual expenditure in a country with an average carbon intensity of 0.53 kgCO_2/USD.

[25] Many approaches are plausible for assessing and comparing heterogeneity within and across expenditure quintiles. For example, Cronin et al. (2019) examines the standard deviation of additional costs.

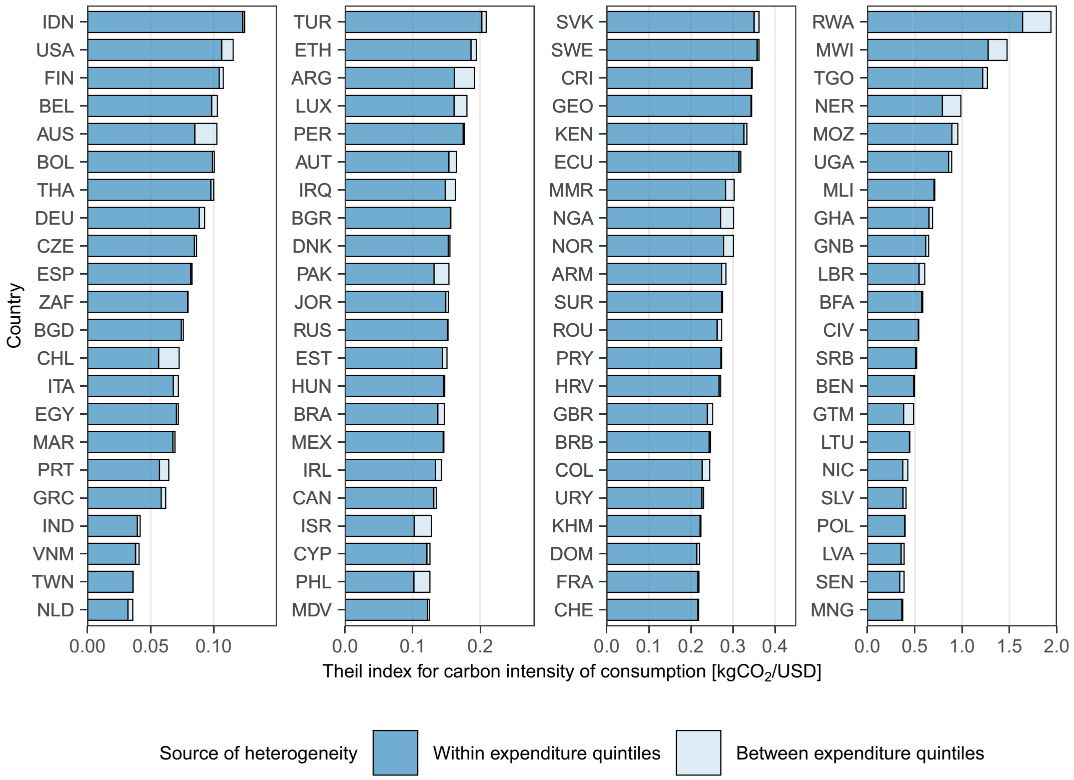

Fig. 1. Heterogeneity in carbon intensity (Theil index) distinguishing between and within expenditure quintile heterogeneity. Bars show the Theil index of carbon intensity of consumption for 88 countries. A Theil index of zero indicates perfect homogeneity and the index increases with increasing overall heterogeneity. Countries are sorted by overall heterogeneity. For each country, bars indicate the heterogeneity that can be attributed to heterogeneity within expenditure quintiles (horizontal heterogeneity) and to heterogeneity between expenditure quintiles (vertical heterogeneity). See also Table A.9.

The *horizontal distribution coefficient* $\widehat{H}_r$ compares within-quintile differences (expressed as the difference between the 5th and the 95th percentiles within quintiles) of the poorest and the richest expenditure quintiles:

$$\widehat{H}_r = \frac{e^{95}_{q1} - e^{5}_{q1}}{e^{95}_{q5} - e^{5}_{q5}} \tag{9}$$

$\widehat{H}_r > 1$ ($\widehat{H}_r < 1$) would indicate that within-quintile differences are greater (smaller) for poorer than for richer households, with implications for the effectiveness of compensation measures differentiated by household income.

3.3. Analysis of heterogeneity in carbon intensity

Fig. 1 shows that horizontal heterogeneity in carbon intensity is consistently greater than vertical heterogeneity. This implies that differences in household income cannot explain all the differences in households' carbon intensity. In response, we analyze the relationship between e_i, the carbon intensity of household i, and observable household characteristics X_i', including but not limited to total household expenditures. We assume that such a relationship exists, i.e., that differences in X_i' are meaningful for explaining differences in e_i:

$$X_i' \sim e_i \tag{10}$$

To shed light on which household characteristics are correlated with, and possibly lead to, higher carbon intensity of consumption, we build on boosted regression trees (BRT).

Boosted regression trees (BRT). Fitting boosted regression trees (Friedman and Meulman, 2003; Elith et al., 2008) is a supervised machine learning method that allows detection of non-linear relationships and interaction effects between an outcome and many predictor variables (*features*). As an extension to regression trees, the BRT algorithm (`XGBoost` by Chen et al. (2016)) fits a sequence of many individual regression trees, iteratively focusing more strongly on observations with larger prediction errors in previous iterations. This results in high predictive power, even compared to the popular random forest algorithm (e.g., Bentéjac et al., 2021).

Drawing on BRT serves the purpose of our analysis because it is a priori ambiguous which variables warrant inclusion in our model. In addition, research suggests that the impacts of climate policy (and thus the carbon intensity of consumption) are distributed non-linearly across households with different characteristics, such as income, demographic groups (Missbach et al., 2023), energy use

(Farrell, 2017), and location (Chan and Sayre, 2023). Unlike other approaches, such as variance-based inequality decomposition (Farrell, 2017; Sager, 2019; Missbach et al., 2024), fitting BRT is well suited to help identify important predictors while accounting for non-linear relationships and interaction effects between variables.

We fit BRT models at the country level to examine characteristics associated with heterogeneous levels of carbon intensity within individual countries. Carbon intensity e_i is the outcome variable. For each country-level model, we use the full (*rich*) set of household-level characteristics $X_i^{\prime}$ as possible features and perform several feature engineering steps (see also Appendix A.3).[26] In addition, we include only total household expenditures as a single feature for prediction in a *sparse* model. Comparing sparse and rich models helps to distill the contribution of additional features in explaining horizontal heterogeneity, i.e., heterogeneity that cannot be explained by heterogeneity in income, yet extends the analysis in Fig. 1 by making use of expenditure differences at the household level. Table A.10 documents all the features used to predict e_i.

The predictive performance of BRT models depends critically on several hyperparameters. For hyperparameter tuning, we use fivefold cross-validation on each country-level subset of the data; we fit 1,000 trees – following the recommendations of Elith et al. (2008) – along with 100 different combinations of learning rate, maximum depth of trees, and fraction of features contained in each tree.[27] For each country, we select the combination of hyperparameters that minimizes the mean absolute error (MAE).

Following the selection of hyperparameters, we use fivefold cross-validation for model evaluation. We evaluate model performance using MAE, root mean squared error (RMSE), and goodness of fit (R^2).

We also use all observations to evaluate the relative importance of each feature using SHAP (SHapley Additive exPlanations) values (Lundberg and Lee, 2017): Expressed in the unit of the outcome variable, SHAP values represent the contribution of each feature to each individual prediction. SHAP values have been proposed as a more appropriate means of interpreting machine learning models compared to other approaches because of improved accuracy, consistency, and interpretability (Lundberg et al., 2020). Based on the SHAP values for all features and individual predictions, we calculate the average absolute SHAP value for each feature across all predictions, which can be interpreted as *feature importance*. Higher average SHAP values indicate that differences in a feature contribute more to the prediction of the outcome variable. We express feature importance as a share of contribution (in % of total average absolute SHAP values) to allow for better comparability of feature importance across countries. In addition, we visualize the distribution of SHAP values for the most important features in each country over feature values using partial dependence plots.

Identification of descriptive country clusters. Country-level analyses can be useful to identify country-specific household characteristics that are associated with higher carbon intensity of consumption. To describe similarities and differences in the importance of characteristics across many countries, we seek to identify illustrative clusters of countries. We do not aim to identify sharply delineated country types, but rather to provide a stylized summary of cross-country patterns concerning the most important features for predicting carbon intensity of consumption.

We adjust for the importance of individual features using country-level goodness of fit (R^2) to account for differences in available features across countries (see also Figure A.1.3). Based on the (adjusted) feature importance measure for each country, we use the k-means algorithm (MacQueen, 1967) for clustering on normalized feature values. Using average silhouette widths (Rousseeuw, 1987), we identify $k = 10$ as the optimal number of clusters. Within the same cluster, individual features are similarly important in predicting households' carbon intensity. We use such descriptive country clusters primarily for visualization of feature importance. More information on the clustering exercise and supplementary robustness checks can be found in the Appendix A.4.

3.4. Methodological limitations

While our approach can serve as a consistent method for studying heterogeneous impacts of climate policy, some methodological aspects are limitations and thus warrant attention.

For example, the use of expenditure survey data is susceptible to many oft-described inaccuracies: such data are prone to underreporting (Meyer et al., 2015), exclude the top end of the income distribution (Blanchet et al., 2022), and reflect consumer prices and policy regimes in the respective survey years. Our approach also neglects within-sector differences in the carbon intensity of consumption and relies on consumer price-dependent *expenditures* to calculate household-level carbon intensity instead of the quality and quantity of consumption. This means that we systematically overlook the consumption of goods and services traded on informal markets, which may be justifiable, given that the additional costs of climate policy are most likely to occur through formal consumption.

Household-level expenditure data may also suffer from measurement error, which can affect the analysis of horizontal heterogeneity.[28] Fortunately, our approach can address this concern, since the adjusted feature importance would be negligible if differences in expenditure shares between households were not correlated with differences in feature values, contrary to the assumption made in Proposition 10.

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[26] All models include household survey weights, which we have normalized and trimmed at the 99th percentile level.

[27] We combine different values for learning rate ($\eta \in [0.001, 0.1]$), maximum depth of trees (`max_depth` $\in \{x \in \mathbb{N} \mid 3 \leq x \leq 15\}$), and fraction of features contained in each tree (`mtry` $\in \{0.5, 0.7, 1\}$). We select randomized combinations of hyperparameters such that the combinations are evenly distributed across the possible combination space using the function `grid_space_filling()` from the *tidymodels* package in R. We show the resulting and preferred combination of hyperparameters in Table A.11.

[28] However, if there is no credible reason to assume that the measurement error of expenditure shares correlates with total household expenditures, then measures of horizontal heterogeneity express heterogeneous consumption behavior for different income groups.

Our approach allows for a consistent, harmonized analysis across countries, but falls short of accounting for the deployment of cleaner technologies since 2017. As a (partial) remedy, we offer analyses for climate policy in the electricity and transport sectors, which can help infer about the direction of changes induced by recent technological change. Also, our analysis may be well suited to informing about the immediate impacts of climate policy, but neglects medium-term effects that occur in general equilibrium.[29]

An important caveat is that our modeling approach does not lend itself to causal interpretation, particularly because we are examining cross-sectional variation. Instead, we attempt to provide an accurate description of household characteristics that are correlated with households' carbon intensity, including non-linear relationships.[30]

The collection of household-level data from different datasets makes it difficult to compare model results across countries because some features are missing in some countries. In response, we adjust the importance of features for model accuracy, but it cannot be concluded from our results that carbon intensity is unpredictable *per se* when model accuracy is low. Some important features remain structurally unobserved by us, but not by governments or other actors interested in our results. For some countries, more nuanced data may therefore help to flesh out more comprehensive analyses. The availability of data also influences our descriptive clustering approach. To avoid the pitfall of countries ending up in one cluster simply because features are missing in the data, we adjust the importance of features for model accuracy. Arguing that we include all relevant and available criteria while minimizing redundancy, clustering can be useful to illustrate similarities in divergence.

4. Results: Predictors of heterogeneous carbon intensity of consumption

Climate policy can lead to short-term costs that are unevenly distributed across the population, depending on the heterogeneity in the carbon intensity of consumption at the household level. Identifying household characteristics (including total household expenditures) that correlate with households' carbon intensity helps to understand this heterogeneity. In the following, we compare the vertical and horizontal distributional effects of climate policy across countries and policy instruments with different regional and sectoral coverage. In addition, we analyze a set of household characteristics and their importance in predicting households' carbon intensity.

The vertical and horizontal distributional effects of climate policy. We start by analyzing the vertical and horizontal distributional effects of climate policy using country-level distribution coefficients that express differences between the poorest and richest quintiles. Fig. 2 shows that the median carbon intensity of consumption in the poorest quintile is greater than in the richest quintile ($\widehat{V}_r > 1$) in 49 out of 88 countries. These countries are relatively more affluent than others, as evidenced by higher GDP per capita: We document $\widehat{V}_r > 1$ for the 24 countries in our sample with the highest GDP per capita. In such comparatively richer countries, climate policy is likely to have regressive effects. In contrast, the median carbon intensity of the richest quintile is higher than that of the poorest quintile ($\widehat{V}_r < 1$) in 19 of the 20 countries with the lowest GDP per capita in our sample. In such comparatively poorer countries, climate policy is likely to have progressive effects. Both findings are consistent with inverted U-shaped Engel curves for carbon-intensive goods and services across countries and income quintiles (Dorband et al., 2019).

Fig. 2 also shows that within-quintile heterogeneity in carbon intensity is greater in the poorest quintile than in the richest quintile ($\widehat{H}_r > 1$) in 60 out of 88 countries. This implies a more heterogeneous distribution of costs among poorer households, especially in richer countries, where climate policy is also more likely to be regressive. The comparison of the two distribution coefficients also shows that differences in horizontal heterogeneity between quintiles exceed vertical differences, i.e., between-quintile heterogeneity, in 70 countries. In other words, within-quintile group differences are larger for poorer households than for richer households. This reinforces the need for a detailed examination of household characteristics associated with higher carbon intensity of consumption beyond differences in household income.

Comparison of climate policy instruments with different sectoral and regional coverage. Our analysis in Fig. 2 describes the distributional effects of climate policy instruments that lead to marginal increases in the price of national CO_2 emissions across all sectors. In essence, climate policy is likely to be more regressive in richer countries and more progressive in poorer countries. Heterogeneity is often greater among poorer households than among richer households, but in general the distributional effects of climate policy appear to depend on country-level circumstances. Supplementary Figure A.6 and Table A.19 show that such distributional effects are also policy-specific, i.e., they differ for policy instruments with different regional or sectoral coverage.

For example, policy instruments that lead to marginal price increases for global CO_2 emissions, such as border carbon adjustment (e.g., Mehling et al., 2019; Cosbey et al., 2019), would lead to increasing heterogeneity among richer households relative to poorer households in 60 countries because richer households tend to spend relatively more on imported goods and services. For transport sector policies, we document more carbon-intensive consumption among richer households compared to poorer households in 60 countries, while differences in horizontal heterogeneity exceed vertical differences in 78 countries.

In contrast, electricity sector policies are likely to affect poorer households more in 61 countries, with greater horizontal heterogeneity among poorer households in 64 countries. These results also inform us about the effects of deploying cleaner technologies.

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[29] Such medium-term effects depend inter alia on pass-through rates in industries, fuel prices or technological substitutes and thus demand-side elasticities. Including general equilibrium effects was found to lead to lower additional costs and less regressive results compared to short-term impacts (Ohlendorf et al., 2021; Drupp et al., 2024).

[30] For example, our analysis should not be read to imply that better education inevitably *leads* to a lower carbon intensity of consumption, but rather that households that consume less carbon-intensively are often better educated, controlling for other important predictors and interaction effects.

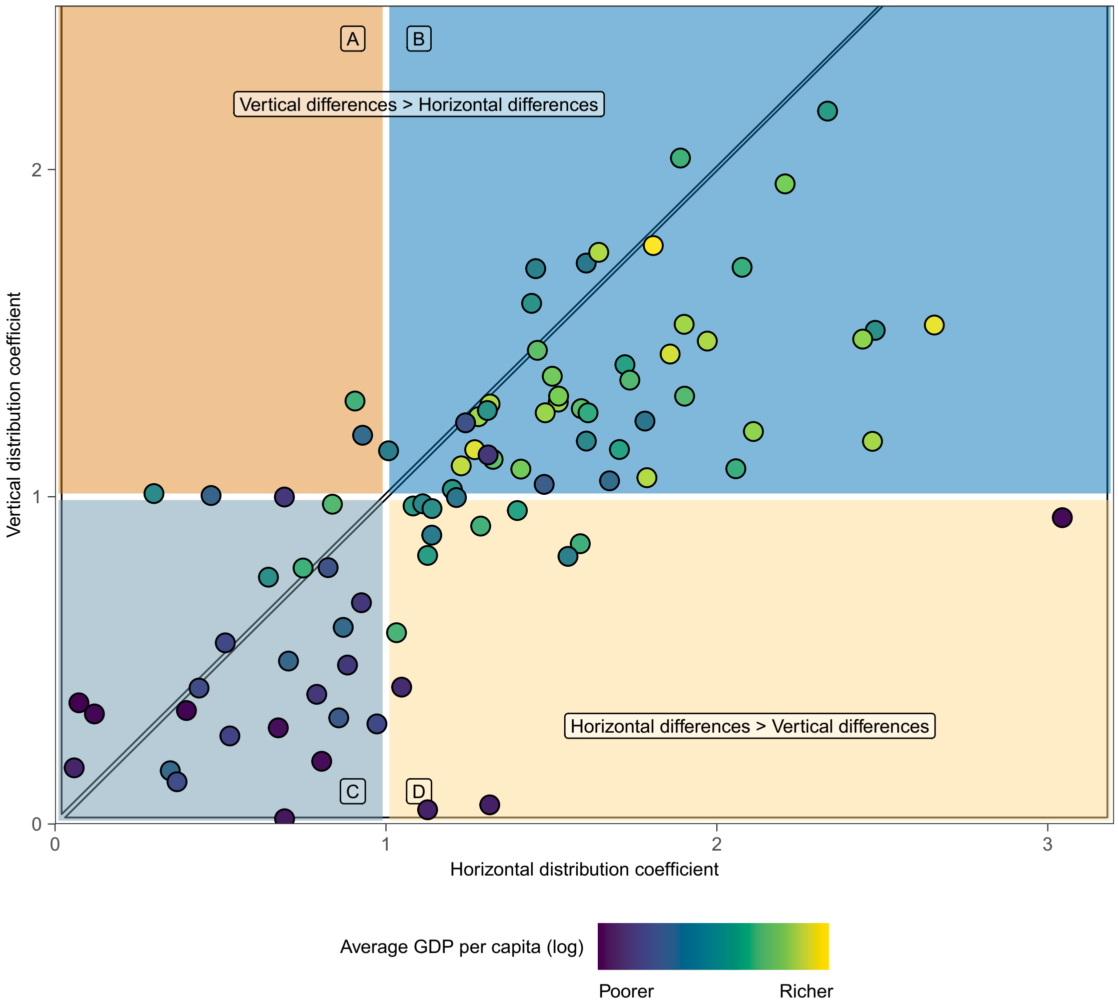

Fig. 2. Vertical and horizontal distribution coefficients. The vertical distribution coefficient (y-axis) compares the median carbon intensity of the richest and poorest quintiles. The horizontal distribution coefficient (x-axis) compares the within-quintile differences (5th to 95th percentiles within quintiles) of the richest and poorest quintiles. Rectangles (A) and (B) indicate higher carbon intensity (at the median) in the poorest quintile compared to the richest quintile; rectangles (C) and (D) indicate lower carbon intensity (at the median) in the poorest quintile compared to the richest quintile. Rectangles (A) and (C) indicate smaller within-quintile differences in carbon intensity among the poorest quintile compared to the richest quintile; rectangles (B) and (D) indicate larger within-quintile differences in carbon intensity among the poorest quintile compared to the richest quintile. Point colors indicate GDP per capita for 2018 (in log-transformed constant 2010 USD). Table A.12 lists both distribution coefficients for all countries and also shows an alternative measure for $\widehat{H}_r$, i.e., comparing the difference between the 20th and 80th within-quintile percentiles for the poorest and the richest quintiles.

Lowering the CO_2 emissions intensity in the electricity sector is likely to lead to less regressive effects and less heterogeneity among poorer households in many contexts. Exemptions include many comparatively poorer countries, where expenditure shares on electricity tend to increase with increasing income.

Comparing the coefficients for vertical and horizontal distributional effects across countries and for policy instruments with different regional and sectoral coverage shows that the distributional impacts of climate policy are country- and importantly policy-specific. This implies that governments may prefer some climate policies over others because of distributional concerns, irrespective of the compensation measures available.

Analysis of heterogeneity: Model accuracy. By analyzing whether household characteristics help explain variation in carbon intensity, we can learn whether compensation policies can effectively compensate households for additional costs. We are thus interested in model accuracy as an important metric.[31] If a model is good at predicting households' carbon intensity based on household characteristics, governments may be more likely to compensate households with high accuracy, if transfers are differentiated based on important features.

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[31] Specifically, goodness of fit (R^2) has a convenient interpretation. For any government that chooses a set of compensating transfers, the goodness of fit indicates the maximum possible reduction in overall heterogeneity in % compared to the policy impact without compensation.

We show that variation in total household expenditures alone is often insufficient to predict households' carbon intensity with high accuracy. On average, the goodness of fit (R^2) accumulates to 6% for *sparse* BRT models including only total household expenditures (see Figure A.7 or Table A.13). In 72 countries, such sparse models contribute to explaining no more than 10% of the variation in carbon intensity. This implies that compensation measures based on household expenditures, such as uniform or income-differentiated cash transfers, but also reductions in consumption taxes, would prove ineffective in compensating households with the highest additional costs.

In contrast, our analyses suggest that including additional features increases model accuracy. On average, R^2 is 24% for *rich* BRT models that include many features in addition to total household expenditures. The accuracy of rich models increases substantially compared to sparse models, for example from 3% to 58% (R^2) in the case of Jordan. Overall, rich BRT models help to predict households' carbon intensity with reasonable accuracy in many countries. Rich models' R^2 accumulates to 59% for Jordan, 49% for Nicaragua, Rwanda and Niger, and exceeds 30% in 28 countries (Table A.13).

For some countries, however, the accuracy of rich models is comparatively low. In 16 countries, R^2 does not exceed 10%. Model accuracy is lowest in Bulgaria and Suriname (1%). One reason is that model performance depends critically on data granularity. In cases of low model accuracy, our models are limited to relying on a few available features, such as household expenditures, sub-national area identifiers, household size, or education of the household head. Nevertheless, low model accuracy implies that in some countries it is difficult to infer about households' carbon intensity from observable characteristics, including total household expenditures. In Bulgaria, for example, vertical differences are small ($\widehat{V}_r^1 = 1.02$) and horizontal differences within expenditure quintiles are comparatively large ($\widehat{H}_r^1 = 1.20$, see also Figure A.4.3). Moreover, as our analysis confirms, within-quintile variation in total household expenditures is largely uncorrelated with variation in carbon intensity, providing additional motivation to analyze heterogeneity in policy impacts beyond (vertical) differences in affluence.

Country-level feature importance. The importance of features in predicting variation in carbon intensity differs across countries. Fig. 3 and Table A.14 show the adjusted feature importance for all features in each country, our vertical distribution coefficient, mean CO_2 intensity, the share of vertical heterogeneity in overall heterogeneity, and R^2, grouped by country clusters for illustrative purposes.[32] While examining feature importance helps to identify features that explain the heterogeneity in carbon intensity, we also consider the contribution to the predicted outcomes for different feature values, as visualized for each country in supplementary partial dependence plots (see Figure A.9).

Without adjusting for model accuracy, the most important feature across countries is total household expenditures, with a relative contribution of 24% on average. Household expenditures are the single most important feature for prediction in 29 countries, and in some countries, such as Luxembourg and Ireland, differences in household expenditures contribute more than 50% to model prediction. Adjusting for model accuracy, household expenditures contribute most to prediction in Iraq (14%), Israel (13%), and Australia (13%) – countries in which we also consistently find higher carbon intensities for poorer households compared to richer households. The relationship between household expenditures and carbon intensity is non-linear, but overall decreasing for 58 countries, overall increasing for eight countries, following an inverted U-shape for 16 countries and a U-shape for six countries (see Figure A.9). We find strictly decreasing relationships between household expenditures and carbon intensity for 19 of the 20 countries with the highest GDP per capita, lending credibility to our descriptive analysis of vertical and horizontal distributional effects. In such countries, more carbon-intensively consuming households spend *absolutely less* on consumption, but *relatively more* on carbon-intensive goods and services.

Motorcycle and car ownership is the most important feature in 13 and 15 countries, respectively. In Niger, Burkina Faso, and Togo, variation in motorcycle ownership accounts for more than 20% of the variation in carbon intensity. Car ownership accounts for the largest adjusted feature importance in Jordan (34%) and Taiwan (19%). On average, vehicle ownership is the most important feature across all countries and features *including* adjustment for model performance. Vehicle ownership can be a strong predictor of climate policy costs in some countries: Households that own motorcycles or cars are more likely to consume more carbon-intensively than households without such vehicles in every country in our sample. This is related to the propensity of vehicle-owning (and -using) households to consume relatively more transportation fuels than others.

Spatial features such as urban or rural location, state, province, or district of the household are the most important features in 13 countries. For example, differentiating between urban and rural households contributes more than 40% of the model prediction in countries such as Latvia, Sweden, and the Czech Republic. In general, we find that urban households consume less carbon-intensively than rural households (for example in Brazil, Morocco, and the United States), and more carbon-intensively in 10 countries (such as Mongolia, Pakistan, and Croatia). In Mongolia, state of residence accounts for 13% of the adjusted feature importance. In Armenia, region of residence accounts for an adjusted feature importance of 4%. Differences in carbon intensity across space suggest an important role for access to energy and transport infrastructure. In many cities, for example, households can choose between different modes of transport, including public transport, which may help to explain the lower carbon intensities of urban households in relatively richer countries. In poorer countries, however, living in urban areas may be associated with more carbon-intensive lifestyles, partly explained by better access to electricity and formal fuels. This may explain more carbon-intensive consumption in urban households in Mongolia, Pakistan, and Croatia, where the data lack features describing energy access that could account for differences between urban and rural households.

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[32] See Table A.15 and Figure A.8.2 for the unadjusted feature importance for all features in each country. See Table A.16 and Figure A.8.3 for the adjusted and imputed feature importance for all features in each country.

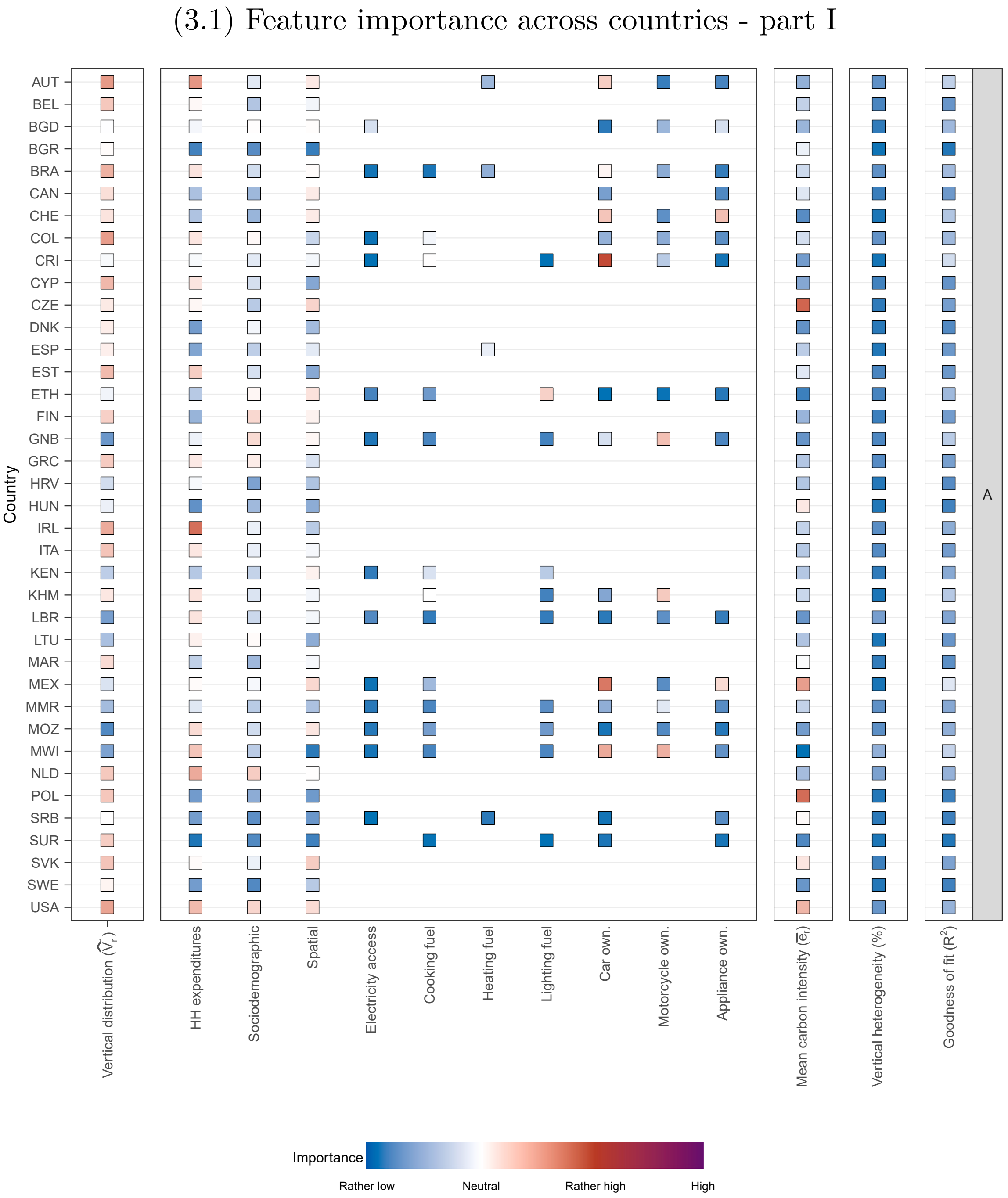

Fig. 3. Feature importance across countries. This figure shows the importance of features (in normalized average absolute SHAP values) for each country, grouped by stylized country clusters. Blue (red) colors indicate that a feature is relatively less (more) important in a country compared to all other countries and features. ‘Sociodemographic’ includes features such as household size, gender, self-identified ethnicity, nationality, religion, and language. ‘Spatial’ includes features such as state, province, district, and urban/rural identifiers. For vertical distribution, blue (red) colors indicate a lower (higher) median carbon intensity in the poorest quintile compared to the richest quintile. For average carbon intensity, blue (red) colors indicate a lower (higher) average carbon intensity across all countries. For the share of vertical heterogeneity in overall heterogeneity, blue (red) colors indicate a lower (higher) share across all countries. For goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity, the share of vertical heterogeneity in overall heterogeneity and R^2 are not explicitly used for clustering. For the purpose of illustration, we assign countries to ten clusters using k-means clustering based on scaled feature importance, adjusted for model accuracy. We also report all values in Table A.14. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

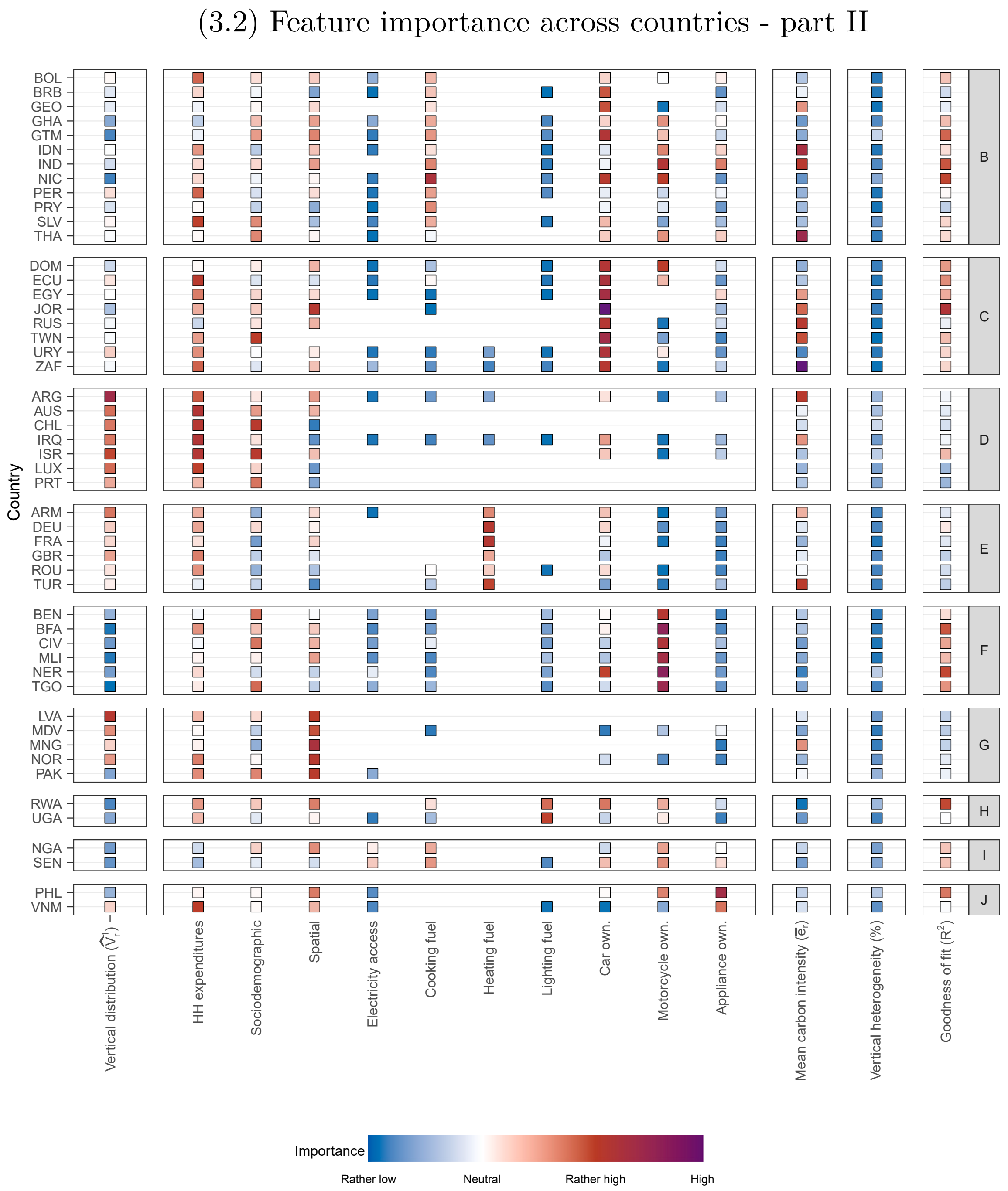
(3.2) Feature importance across countries - part II

Fig. 3. (Continued).

Information on energy use, such as the main fuels used for cooking, lighting, and heating, or electricity access and appliance ownership, is the most important feature in twelve of the countries where such features are available. Main cooking fuel is an important feature in Nicaragua and India, with an adjusted feature importance of 15% and 8%, respectively. In both countries, households that cook with LPG consume substantially more carbon-intensively than households that cook predominantly with firewood, a pattern that is consistent across all countries in our sample where a non-negligible share of households use firewood or charcoal for cooking. This result is in line with our assumption of zero direct emissions from biomass, firewood, and charcoal because of informal markets and structural impediments to regulating (and taxing) emissions from these sources.[33] The use of kerosene for lighting is associated

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[33] In addition, our CO_2 emissions data only include emissions from fossil fuels, but not from biomass.

with higher carbon intensity compared to electricity and other lighting sources in Uganda, Rwanda, and Ethiopia with an adjusted feature importance of 10% for Uganda and 8% for Rwanda. Information on heating fuels is the single most important feature in five countries. Here, carbon intensity is higher in households that heat with coal (Turkey) or natural gas (Armenia, Germany, France, United Kingdom) than in households that heat with electricity. In other countries, such as Spain, Brazil, Austria, and Uruguay, the adjusted feature importance of heating fuels accumulates to no more than 3%.

Overall, electricity access is less frequently an important feature, contributing a maximum of 5% of the adjusted feature importance in Senegal. In the majority of countries, the feature importance for electricity access is low, possibly because of overall high electricity access rates (e.g., Vietnam and the Philippines) or low electricity access rates (e.g., Malawi and Liberia, see Table A.2) or low carbon intensity of the electricity sector (e.g., Ethiopia and Kenya, see Table A.17).

Instead, ownership of major household appliances (such as refrigerators, washing machines, and air conditioners) is the most important feature in Switzerland and the Philippines, accounting for 18% of the adjusted feature performance in the Philippines. This is less surprising because appliance ownership is a more relevant, but incomplete, predictor for electricity *use* than electricity *access*.

Sociodemographic features such as education, gender, self-identified ethnicity, nationality or religion of the household head are the most important features in two countries. In Hungary, for example, where household education accounts for 26% of the model prediction, households with tertiary education have a higher carbon intensity than households with primary or secondary education. The adjusted feature importance for gender of household head is highest in Togo and Benin, where households with female household heads are found to consume less carbon-intensively. In Israel, households that report a traditional, religious, or orthodox lifestyle consume more carbon-intensively than secular households. For 76 out of 88 countries, individual sociodemographic features do not exceed 5% of the adjusted feature importance, indicating their relatively low relevance across countries for predicting differences in carbon intensity.

Descriptive country clusters. For illustrative purposes, we can compare countries with respect to features that are important in predicting differences in carbon intensity. Based on the adjusted importance of all features and the vertical distribution coefficient of countries, we identify ten distinct stylized clusters of countries. Within clusters, countries are more similar to each other than to countries in other clusters.

This illustrative clustering exercise suggests substantial heterogeneity across countries in contribution of observable features to the prediction of carbon intensity in consumption (Figure A.10 and Appendix A.4). In some clusters of countries, household expenditures and spatial characteristics explain comparatively larger shares of variation in our outcome variable. In others, variables describing vehicle ownership, access to electricity, or information about primary fuel use appear to be more relevant. Implicitly, these stylized clusters indicate heterogeneous patterns of consumption and energy use. One implication is that it may be inaccurate to infer the distributional effects of climate policy in one country from the experience of other countries.

Importantly, the model performance and feature availability can vary substantially across countries, which confines our clustering approach to primarily descriptive purposes.

5. Discussion: Policy instruments for effective compensation

Our analysis provides evidence for country-specific household characteristics associated with higher carbon intensity of consumption. Our results can be useful in ex-ante assessments of climate policy to identify particularly affected household profiles and thus effective policies to compensate them. The persistence of heterogeneity that cannot be explained with variation in household expenditures suggests that commonly proposed compensation options, such as uniform lump-sum transfers, may not be effective in compensating the most carbon intensive households. Moreover, most of the discourse on complementary compensation policies focuses on industrialized countries, where, as we show, household characteristics associated with carbon-intensive consumption differ substantially from those in other countries.

Here, we refrain from proposing specific compensation policies for particular countries, and recognize that preferences for specific compensation measures over others are subject to normative considerations at the government level. In general, price-based interventions such as carbon pricing or fossil fuel subsidy removal, might facilitate compensation as they increase the fiscal space to reimburse households. A thorough comparison of different compensation policies should take into account the nature of the existing tax system, the administrative costs of alternative transfer mechanisms, potentially constrained government capacity, and the limited information available to policymakers. With these limitations in mind, we discuss in the following which policy options could be more effective in supporting those households that would bear the highest additional costs, thereby reducing overall heterogeneity.[34]

Uniform lump-sum transfers, potentially distributed equally per capita, are the textbook solution for many economists, preferred specifically for their administrative simplicity and non-distortionary properties. Such transfers would be highly effective, if governments had a strong preference for reducing vertical inequality while avoiding regressive effects[35] and ensuring high salience of

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[34] Our analysis can shed light on *existing* compensation policies for climate policy. The Austrian government, for example, uses carbon pricing revenues to finance lump-sum transfers, which vary across regions. Households living in regions with less transport and health infrastructure receive higher transfers (BMK, 2023). Our analysis shows that household expenditures and spatial features account for 52% of predicted values ($R^2 = 0.21$). Despite some remaining unobserved heterogeneity and the lack of differentiation of transfers with respect to heating fuels and car ownership, this transfer mechanism is likely reducing horizontal heterogeneity.

[35] In this case, Stiglitz (2019) proposes sectorally differentiated regulation, depending on whether richer households disproportionately consume the respective goods and services. This could imply, for example, comparatively stricter intervention in the aviation sector, albeit with aggregate efficiency losses.

compensation (Chetty et al., 2009). In contrast, research draws attention to the relatively low public acceptance of such transfers and the 'equity-pollution-dilemma'[36] (Sager, 2019).

Following our framework in Section 2, uniform lump-sum transfers would be effective in reducing heterogeneous impacts of climate policy in countries where total household expenditures are an important feature and where disproportionately high costs would fall on relatively poorer households. This is because such transfers would lead to higher benefits for poorer households, thus minimizing the naïve incidence for all households. For example, such transfers could be comparatively effective in reducing horizontal heterogeneity in countries such as Argentina, Australia, Chile, or Israel.

Leveraging *cash transfer programs targeting low-income households*, could be convenient, as many governments have established such institutions already, even though targeting errors of cash transfer programs can be substantial (Banerjee et al., 2022; Bah et al., 2019). Such transfers would provide even higher benefits for poorer households, but not for richer households, which leads to more progressive results. With the aim of reducing overall resulting heterogeneity, such transfers targeting low-income households may be helpful, if poorer households consume more carbon-intensively than richer households, but household expenditures are not an important feature. In our sample, this is the case in countries such as Spain, Poland, or Suriname.

The discipline has also popularized *reducing distortionary taxes* to reap a 'double dividend' (Bovenberg and Lawrence, 1996). In addition, lowering income or consumption taxes provides leverage to counter vertical heterogeneity. For example, if richer households consume more carbon-intensively and household expenditures are an important feature, lowering the labor tax may reduce overall heterogeneity effectively because such tax cuts benefit richer households relatively more. Indeed, in some countries, such as Pakistan, Burkina Faso, or Nicaragua, reducing labor taxes may be useful for effective compensation while also promoting formalization (Jessen and Kluve, 2021; Rocha et al., 2018) and economic activity (Ulyssea, 2018).

Uniform cuts in excise taxes on consumption, in contrast, benefit all households equally in relative terms, thus not reducing heterogeneity in the naïve incidence at all. Tax reductions differentiated by product (e.g., through VAT), for example through lower tax rates on basic consumer goods, including food and some forms of energy, may reduce heterogeneity, if household expenditures are an important feature and if poorer households consume more carbon-intensively. This is because poorer households spend a larger share of their expenditure on such goods in most contexts.[37] In addition, such differentiated tax reductions could shift consumption towards less carbon-intensive products (Klenert et al., 2023).

Low model accuracy found for some countries implies that the carbon intensity of consumption cannot be predicted with observable characteristics at hand. This implies that any transfer based on characteristics observable in our dataset will be ineffective in compensating the most carbon-intensive households and in reducing overall heterogeneity of incidence. This holds specifically for many countries including Ethiopia ($R^2 = 0.15$), the U.S. ($R^2 = 0.12$), or Italy ($R^2 = 0.10$), underscoring the importance of country- and policy-specific research, especially when governments face information problems (Mirrlees, 1971).

In such circumstances, model accuracy would improve drastically by including household-level expenditure shares on different consumption goods and services as predictors – as these critically determine the carbon intensity of consumption. The corresponding compensation policy would consist of reducing excise taxes on comparatively carbon-intensive goods and services. This could contain overall heterogeneity while preserving incentives for supply-side abatement (Goulder and Parry, 2008), even though such a policy would substantially reduce the overall mitigation effect of climate policy. Thus, excise tax cuts may have their merits specifically to address additional market failures, such as technological lock-ins for cooking fuels, preventing substitution from fossil-based cooking fuels to less expensive, but potentially hazardous biomass (Greve and Lay, 2022).

In countries with large horizontal heterogeneity and low predictive power for total household expenditures, uniform lump-sum transfers and (income or consumption) tax cuts would likely fall short of compensating the most carbon-intensive households. In such circumstances, it may be important to *enable access to low-carbon technologies* for carbon-intensive consumers. This can help increase the (absolute) price elasticity of households and make it easier for households to consume less carbon-intensive goods and services. Where vehicle and appliance ownership is important, lowering technological barriers can be effective in reducing overall heterogeneity, for example through incentives for energy efficiency improvements, improved public transport systems, or investments in green mobility infrastructure. Such policies could reduce the costs for households using specific technologies, which lowers overall heterogeneity. The main cooking fuel is an important feature in countries such as Nicaragua, India, or Peru. Here, subsidies for clean cookstoves or 'transition fuels' (such as LPG) may be effective. From the perspective of reducing distributional effects, exempting kerosene from regulation may be useful in Rwanda and Uganda, while addressing the heating sector through improvements in buildings may be helpful in countries such as Germany, France, or Turkey, where the main heating fuel is an important predictor.

Addressing the heterogeneous impacts of climate mitigation policy does not necessarily require considering different compensation options. Instead, policymakers can also turn to different types of regulation. As we show, increasing the marginal cost of global CO_2 emissions would lead to more heterogeneity among richer households. Transport sector policies would imply more progressive effects, but also more (horizontal) heterogeneity in general. In contrast, electricity sector policies would lead to more regressive effects with

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[36] The 'equity-pollution-dilemma' describes that reducing inequality, e.g., with progressive transfers could increase emissions on aggregate because the average carbon intensity for poorer households is larger than for richer households (see also Stiglitz, 2019). In general, redistribution could partially offset demand-side effects of climate policy. Nevertheless, carbon pricing with cost-equivalent transfers to households would be desirable because carbon pricing shifts relative prices between more and less carbon-intensive goods and services.

[37] If informal consumption is more widespread, however, reducing consumption taxes may be less progressive (Bachas et al., 2020).

greater heterogeneity among poorer households. While we refrain from investigating the importance of household characteristics in predicting the outcomes of such policies for now,[38] our results highlight that addressing unintended distributional impacts may also have implications for the choice of climate policy instruments, albeit with implications for aggregate efficiency and revenue collection.

The interpretation of our findings is relatively straightforward for price-based policies. Nevertheless, our approach can also inform the design of standards, mandates, or subsidies, depending on how such policies affect the marginal cost of CO_2 emissions. However, distributional impacts may be less salient for such instruments, and potential compensation would also be more difficult to finance because of foregone revenues.

Our analysis provides a foundation for more comprehensive analyses[39] using more nuanced data. Such additional research can explicitly address inaccuracies in our modeling approach, including uncertainties about the supply-side pass-through of cost increases, technological path dependencies, and information frictions. Admittedly, our work is also silent on the heterogeneous impacts of climate policy in terms of potential co-benefits (e.g., Holland et al., 2019; Karlsson et al., 2020), co-costs (e.g., Fuje, 2019; Greve and Lay, 2022), wealth (e.g., Fullerton, 2011), and labor (e.g., Castellanos and Heutel, 2024). Instead, this study provides information on the first-order distributional impacts of climate policy on consumption costs, which may be useful for identifying potential demand for compensation and ultimately for increasing public acceptance. Our descriptive clustering of countries demonstrates that some compensation policies would work more effectively in some countries than in others, potentially limiting the scope for cross-country learning.

The distributional impacts of welfare-enhancing policy proposals are important not only for welfare analyses, but also for understanding the political economy of climate policy. While this study provides a comprehensive assessment of such distributional impacts for climate policy, it is less clear how the distribution of costs translates into public *acceptance*. It is often argued that people prefer progressive outcomes because of equity reasons, but large horizontal heterogeneity, subjective beliefs (Douenne and Fabre, 2020), and scattered perceptions of fairness (Maestre-Andrés et al., 2019; Povitkina et al., 2021) cast doubt on this assumption. Future research could contribute to a better understanding of how the (expected) distribution of costs and individual and government-level inequality aversion shape public acceptance of climate policy. Similarly, some policy instruments and complementary compensation measures may be more acceptable to the public than others, but research providing theory and empirical evidence remains scarce (e.g., Sommer et al., 2022; Mohammadzadeh Valencia et al., 2024), at least compared to the literature quantifying distributional impacts.

6. Conclusion

This study provides a detailed analysis of the heterogeneous effects of climate policy on households across 88 countries. Our flexible framework, which integrates multi-regional input–output data with detailed household expenditure data, allows for the analysis of country- and policy-specific impacts. We use supervised machine learning to identify household characteristics that help explain overall variation in the carbon intensity of consumption at the country level.

Our results show that differences in total household expenditures can be important in explaining such variation. However, focusing solely on differences in household expenditures misses relevant parts of the picture. Heterogeneity within expenditure groups substantially outweighs heterogeneity between them and models based on household expenditures are comparatively inaccurate in explaining overall heterogeneity. As we show, the analysis of heterogeneous outcomes of climate policy requires the inclusion of additional, oft-neglected household characteristics, such as information on energy use, vehicle and appliance ownership, location, or sociodemographic characteristics. For each country, we quantify the contribution of individual features and show that their relative importance varies compared to other countries.

The central findings of this work suggest that the heterogeneous impacts of climate policy are country- and policy-specific. In some countries, it is difficult to predict the costs of climate policy based on available household characteristics including household expenditures. This implies that it may be difficult to address vertical and, in particular, horizontal distributional effects of climate policy with commonly proposed measures such as uniform lump-sum transfers. Instead, we identify complementary compensation policies that can help governments more effectively ease the unintended distributional effects of climate policy. This may be an important prerequisite for efficient, yet less unequal and thus more politically acceptable climate change mitigation.

CRediT authorship contribution statement

Leonard Missbach: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Jan Christoph Steckel:** Writing – review & editing, Conceptualization.

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[38] Descriptive analyses for carbon pricing reforms and stylized compensation policies can be accessed and customized through a separate webtool.

[39] For example, fitting a model on observations from multiple countries including country as a feature can have its merits, if regulation affects the population across many countries. For illustrative purposes, we have fitted such a model to countries of the EU (see Figure A.11). Results show that heterogeneity could be reduced most effectively by transfers differentiated by country.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Leonard Missbach reports financial support was provided by Horizon Europe (101056873, ELEVATE and 101069880, AdJUST). Jan Christoph Steckel reports financial support was provided by Horizon Europe (101056873, ELEVATE and 101069880, AdJUST). Leonard Missbach reports financial support was provided by Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ, 812388773, Förderung sozial akzeptierter CO2-Bepreisung). Jan Christoph Steckel reports financial support was provided by Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ, 812388773, Förderung sozial akzeptierter CO2-Bepreisung). Leonard Missbach reports financial support was provided by Federal Ministry of Education and Research (BMBF, 03SFK5J0, Ariadne). Jan Christoph Steckel reports financial support was provided by Federal Ministry of Education and Research (BMBF, 03SFK5J0, Ariadne). Leonard Missbach reports financial support was provided by Deutsche Bundesstiftung Umwelt. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data for this article can be found online at doi:10.1016/j.jeem.2026.103382.

Data availability

More details on data and code can be found at the Supplementary Information document.

Supplementary Table C.1 provides publishing organizations, names of surveys, and links to datasets used in this study. Data from household budget surveys are available from statistical agencies subject to permission and possible allowances.

Data from GTAP are available through GTAP, subject to academic subscription.

We distribute all code written for cleaning and harmonizing household data, modeling carbon intensity of consumption and analysis through GitHub. This repository also contains matching tables for all countries.

Descriptive analyses for carbon pricing reforms and stylized compensation policies can be accessed and customized through a separate webtool.

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