Distributional impacts of climate policy and effective compensation: Evidence from 88 countries

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Abstract

We analyze the distributional impacts 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 1.5 million individual households from 88 countries. We first show that horizontal differences are generally larger than vertical differences. We then use supervised machine learning to analyze the non-linear contribution of household characteristics to the prediction of carbon intensity of consumption. Including household-level information beyond total household expenditures, such as information on vehicle ownership, location, and energy use, increases the accuracy of predicting households' carbon intensity. The importance of such features is country-specific and model accuracy varies across the sample. We identify six clusters of countries that differ in the distribution of climate policy costs and their determinants. Our results highlight that, depending on the context, some compensation policies may be more effective in reducing horizontal heterogeneity than others.

Keywords: Climate policy, Distributional effects, Inequality, Transfers
JEL Codes: C38, C55, D30, H23, Q56

1 Introduction

Both policymakers and the public often judge a policy by its distributional implications. One reason for this is that the distribution of policy-induced costs across household groups can influence overall public acceptance and thus the political feasibility of policy reforms. In the context of climate change mitigation, unintended and heterogeneous policy impacts on households have been associated with public opposition (Maestre-Andrés et al. 2019; Dechezleprêtre et al. 2022), ultimately limiting the implementation of efficient and effective mitigation policies (Clements et al. 2013; Douenne 2020).

In theory, it is possible to alleviate distributional impacts by complementing climate policy with compensation policies. In practice, however, governments face important information constraints. It is often unclear ex ante 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 can reduce the effectiveness of oft-proposed uniform lump-sum transfers. Effective compensation, however, i.e., minimizing targeting errors, is important to advance public support for climate policy and to ease fiscal pressures. Yet, our understanding of which compensation policies would be effective in achieving which distribution of costs *post*-compensation is crude.

In this study, we analyze the heterogeneous impacts of climate policy instruments on households in 88 countries. We go beyond traditional analyses of vertical and horizontal heterogeneity and use supervised machine learning to disentangle the non-linear contribution of household characteristics to variation in the carbon intensity of consumption. The carbon intensity of consumption serves as an accurate representation of the short-term additional costs of climate policy, at least for any policy instrument that increases the marginal cost of emitting CO_2.

We show that across the entire sample, horizontal differences in carbon intensity within income groups exceed vertical differences between income groups. Heterogeneity in income, proxied by total household expenditures, is often insufficient by itself to predict heterogeneity in carbon intensity. Instead, other important household characteristics beyond household expenditures include vehicle ownership, information on household location, and energy use, such as main cooking and heating fuels and appliance ownership. Including such characteristics in our models substantially improves our prediction of households' carbon intensity. Our results point to country- and policy-specific distributional impacts that call for compensation policies tailored to each country context if households are to be effectively compensated for additional costs, thereby reducing horizontal heterogeneity.

Our contribution to a more comprehensive assessment of the heterogeneous impacts of climate policy is threefold: First, we compile a novel and harmonized dataset on the carbon intensity of consumption at the household level. Our dataset contains granular information on 1.5 million individual households, representing more than 5 billion people in 88 countries. In contrast, previous work often focuses on single-country contexts or neglects within-country characteristics at the household level. Second, we use supervised machine learning to identify non-linear relationships between household characteristics and carbon intensity of consumption, while the (nascent) literature on horizontal heterogeneity focuses primarily on linear models. Third, we identify different clusters of countries based on the model results. Countries in the same cluster are more similar to each other with respect to factors associated with the heterogeneity in carbon intensity. This approach contributes to a more systematic understanding of similarities and differences in country-specific characteristics of distributional impacts.

We proceed as follows: In Chapter 2, we present a theoretical framework describing the distributional impacts of climate policy and their relevance for governments to design complementary compensation policies. In Chapter 3, we present our modeling approach, which combines household budget survey and multi-regional input-output data. We present empirical methods to describe both within-country heterogeneity and cross-country similarities. In Chapter 4, we analyze the vertical and horizontal distributional effects of climate policy, describe the relative importance of household characteristics for predicting carbon intensity at the country level, and cluster countries when household characteristics are similarly important. Finally, we discuss our findings in light of ongoing debates about how to avoid or address unintended distributional impacts of climate policy in Chapter 5 before concluding in Chapter 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. This implies that we ignore government preferences for more stringent climate policy, as well as the benefits of abated climate change and their distribution across households. 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 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 $c_{i,p} < 0$ 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. 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 wealth. 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 for 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 (Dorband et al. 2019; Jacobs and van der Ploeg 2019). Both household income and the use of less polluting technologies are part of a set of household characteristics X_i.

Governments thus choose a set of climate policy instruments P' that leads 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 $b_{i,t} > 0$ 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[1].

[1]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

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; Bah et al. 2019; Robles et al. 2019). Reasons for this include 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 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 (Baranzini et al. 2000; Metcalf 2009; Stiglitz et al. 2017; Sager 2023), precisely because governments require little information about the recipients and because such transfers feature easing 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: Financing public infrastructure may help promote development goals (Jakob et al. 2016; Franks et al. 2018), subsidizing or providing subsistence goods (including energy) may prevent adverse effects on the poorest households (Schaffitzel et al. 2019; Greve and Lay 2022), and green spending may lead to increased public support (Kotchen et al. 2017; Dechezleprêtre et al. 2022; Sommer et al. 2022). 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[2].

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

$$\pi_i = \underbrace{\sum_{P'} c_{i,P'}}_{\text{costs from climate policy}} + \underbrace{\sum_{T} b_{i,T} + b_{i,\varepsilon}}_{\text{benefits from compensation policy}} \tag{1}$$

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

benefits to environmental attitudes or the use of efficient appliances.

[2]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.

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 additional costs $c_{P'}$ are 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. 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.

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:

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

$\overline{\pi_{q_i}}$ 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. 2022). 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.

Many researchers have studied the vertical distributional effects of climate policy instruments, i.e., heterogeneity in policy outcomes between relatively poorer and relatively richer households[3]. For price-based climate policy instruments (such as carbon pricing), such work includes analyses in single countries (Poterba 1991; Grainger and Kolstad

[3]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, including in particular household investment decisions, and finds that *carbon inequality* within countries has increased over the last thirty years. Others (Oswald 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.

2010; Rausch et al. 2011; Sterner 2012; Goulder et al. 2019; Garaffa et al. 2021; 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. In contrast, a meta-analysis (Ohlendorf et al. 2021) documents more progressive results in lower-income countries and for price-based policies aimed at the transport sector.

Another strand of research explores vertical distributional impacts for other climate policy instruments, such as fossil fuel subsidy removal (Del Arze Granado et al. 2012; Schaffitzel et al. 2019; Giuliano et al. 2020), technology standards (Bruegge et al. 2019; Levinson 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.

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:

$$H_i = \sum_q \delta_{i,q}^H * H_q \tag{3}$$

H_q denotes differences in additional costs within income groups. One measure of H_q can be the difference between the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles in each income group, i.e., $H_q = \pi_q^{95} - \pi_q^5$. Variable $\delta_{i,q}^H$ 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., $\frac{\pi_{i,q}}{\overline{\pi_q}}$. Similarly, variable $\delta_{i,q}^H$ 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 (Burtraw et al. 2009; Chan and Sayre 2023), 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 would 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 maximizes public acceptance when faced with an exogenous target to reduce CO_2 emissions. 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[4]. We express the government decision problem as follows:

$$\max_{P',T} \Theta = \sum_i \mu_i * \rho_i(\pi_i + V_i + H_i) \tag{4}$$

The term $(\pi_i + V_i + H_i)$ 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. 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

[4]The medium-term costs to households depend critically on substitution elasticities and thus implicitly on available technologies and existing infrastructure.

least distributive distortions (Fischer and Pizer 2019) or that governments reject policies that increase inequality *per se*. 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 and Rogers 2016; Hänsel et al. 2022) because some households have access to less carbon-intensive technologies and others do not, implying that efficiency-enhancing climate policies may lead to increased inequality. Equation 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 Equation 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 systematically describe the vertical and horizontal distributional effects of climate policy, i.e., we compare additional costs across and within income groups. Third, we analyze which compensating policies would be effective in solving the government decision problem by reducing vertical and, in particular, horizontal distributional effects. Implicitly, we ask: Which household characteristics X' can help explain the variation in additional costs c_p? This may have different 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[5].

[5]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

In this chapter, we first describe the construction of a novel dataset that captures household-level carbon intensities across countries[6]. 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 intensity.

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[7] CO_2 emissions E_i in household i relative to total consumption C_i and thus the additional cost of climate policy at the household level $c_{i,p}$, as described in Chapter 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 $w_{i,s}$:

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

Examining the carbon intensity at the household level for different sectors s, denoted by $e_{i,s}$, 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 ($w_{i,s} = \frac{C_{i,s}}{\sum_s C_{i,s}}$) from household budget surveys (see Table C.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[8]. We include survey datasets in our study if they cover a nationally representative sample, include item-level

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. A visible example is an upstream carbon tax. See also Appendix A.4.

[6]Supplementary Figure B.1 visualizes key elements of our data work and analyses.

[7]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.

[8]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 B.2 shows country-level Engel curves for energy, goods, services, and food.

expenditure information, and if the surveys were conducted between 2010 and 2019[9]. After several cleaning steps[10], our resulting dataset contains information on more than 1.5 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[11].

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[12].

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[13].

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

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

We derive total sectoral consumption ($\sum_i C_{i,s,r}$), direct (E_s^{direct}) and indirect ($E_s^{indirect}$) CO_2 emissions from multi-regional input-output (MRIO) data. This approach is popular among researchers because it accounts for trade flows between different countries and regions, while providing sufficient detail for high sectoral resolution.

We capitalize on trade data from the GTAP database (Version 11B, Aguiar et al.

[9] 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.

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

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

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

[13] Table C.2 shows summary statistics for all countries in our sample; Table C.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 C.4) and lighting fuels (Table C.5), and that own various major appliances (Table C.6) for all countries for which such data are available.

2022), which we transform to 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 $E^{indirect}_s$ as follows[14]:

$$E^{indirect}_s = \sum_{r'} \sum_{s'} e_{r',s'} L^{r,s}_{r',s'} C_s \tag{7}$$

In addition, the GTAP database also includes information on direct CO_2 emissions E^{direct}_s. This covers CO_2 emissions resulting from the household-level use of fossil fuels, such as gasoline, natural gas, LPG, and hard coal.

Our result is a matrix containing information on the carbon intensities of (household) consumption $e_{s,r}$ for 65 sectors s and 160 countries r. These data reflect 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 B.3.

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 Equation 5. Specifically, it consists of nationally representative accounts of the carbon intensity of household consumption e_i. 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[15].

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 0.69

[14] See Vogt-Schilb et al. (2019), Feindt et al. (2021), Steckel et al. (2021), and 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.4.

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

$kgCO_2/USD$[16]. The average carbon intensity is highest for South Africa (2.04 $kgCO_2/USD$), followed by Turkey (1.75 $kgCO_2/USD$) and the Czech Republic (1.72 $kgCO_2/USD$). The average carbon intensity is lowest for Malawi (0.03 $kgCO_2/USD$), Rwanda (0.04 $kgCO_2/USD$), Ethiopia and Niger (both 0.1 $kgCO_2/USD$)[17,18].

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 25^{th} or 75^{th} 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.

Figure 1 shows the distribution of carbon intensity of consumption among the poorest quintile in all countries in our sample. Boxes and whiskers contain 90% of all households in each quintile and represent horizontal heterogeneity, i.e., differences among poorer households. In contrast, colored bars show the difference between the lowest and highest median carbon intensity across all quintiles for each country, describing vertical heterogeneity, i.e., differences between poorer and richer households[19].

Figure 1 shows that within-quintile heterogeneity exceeds between-quintile heterogeneity in *all* countries. This highlights the fact that analyses that rely on differences in income to explain differences in the carbon intensity of consumption (or the impact of climate policy) may be inadequate because they do not 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 is also warranted because within-quintile differences may *vary* across quintiles. To facilitate the comparison of vertical and horizontal differences across countries, we abstract from comparisons between all income groups (as in Equations 2 and 3) and introduce two coefficients (Missbach et al. 2024)[20]: The *vertical distribution coefficient*

[16]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.

[17]See Table C.7 for average carbon intensities for all countries.

[18]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 2.76% of total annual expenditure in a country with an average carbon intensity of 0.69 $kgCO_2/USD$.

[19]See Figure B.4 for country-level comparisons across all expenditure quintiles and Table C.7 for summary statistics on carbon footprints and carbon intensity of consumption.

[20]Many approaches are plausible for assessing and comparing heterogeneity within and across expen-

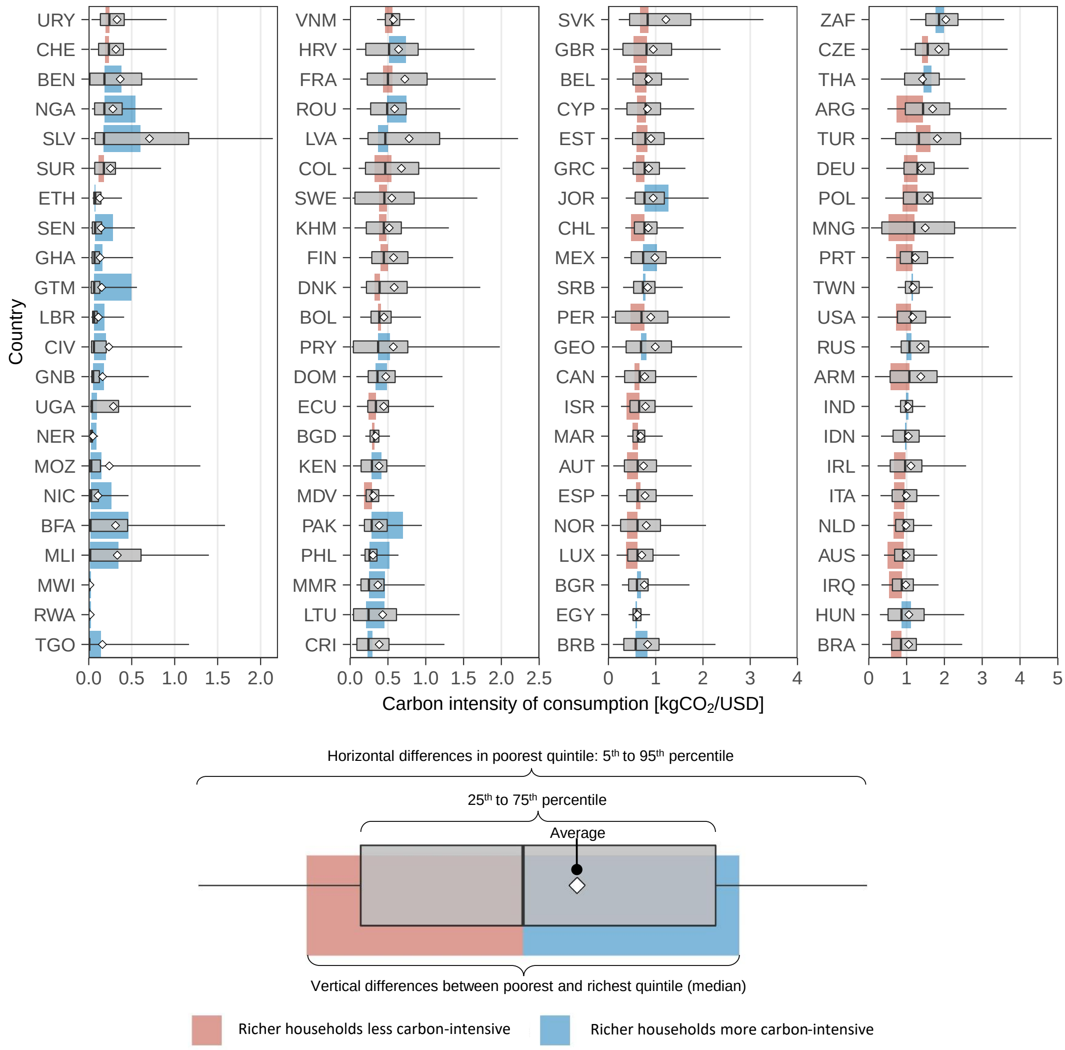


Figure 1: Vertical differences and horizontal distribution of carbon intensity within poorest quintiles

Boxplots show the horizontal distribution of carbon intensity at the household level within the poorest expenditure quintile in each of the 88 countries in our sample: Boxes show the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles; whiskers show the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles, respectively. Rhombuses show the mean. Blue and red bars represent the vertical difference in carbon intensity at the household level, i.e., the difference between the highest and the lowest median carbon intensity across quintiles. Red (blue) bars indicate that richer households consume less (more) carbon-intensively at the median than poorer households. Figure B.4 shows the distribution of carbon intensities for all expenditure quintiles across all countries in our sample. We rank countries from bottom left to top right by the median carbon intensity in the poorest quintile. Note the different x-axes in the different panels.

$\widehat{V_r}$ 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

diture quintiles. For example, Cronin et al. (2019) examine the standard deviation of additional costs.

carbon intensity of richer households, then $\widehat{V_r} > 1$ ($\widehat{V_r} < 1$) and climate policy would likely lead to regressive (progressive) outcomes.

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

$$\widehat{H_r} = \frac{e_{q1}^{95} - e_{q1}^{5}}{e_{q5}^{95} - e_{q5}^{5}} \tag{9}$$

$\widehat{H_r} > 1$ ($\widehat{H_r} < 1$) 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

Figure 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 two analytical approaches, namely boosted regression trees (BRT) and a logit model.

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 and Guestrin (2016)) fits many individual regression trees, iteratively giving higher weights to observations with larger prediction errors. 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' as possible features and perform several feature engineering steps (see also Appendix A.3). 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. Table 1 documents all the features used to predict e_i.

Feature group	Feature	Description	Countries	Sparse	Rich
HH expenditures	Household expenditures	Total household expenditures (USD 2017)	88	Yes	Yes
Sociodemographic	Household size	Number of household members	88	No	Yes
	Gender	Gender of household head	86	No	Yes
	Education	Educational attainment of household head	83	No	Yes
	Ethnicity	Ethnicity of household head	33	No	Yes
	Religion	Religion of household head	21	No	Yes
	Nationality	Nationality of household head	15	No	Yes
	Language	Main language of household head	8	No	Yes
Spatial	Urban	Urban or rural citizenship	79	No	Yes
	Province	Sub-national area identifier	58	No	Yes
	District	Sub-sub-national area identifier	20	No	Yes
Cooking fuel	Main cooking fuel	Fuel used predominantly for cooking	45	No	Yes
Electricity access	Electricity access	Access to electricity grid	44	No	Yes
Lighting fuel	Main lighting fuel	Fuel used predominantly for lighting	34	No	Yes
Heating fuel	Main heating fuel	Fuel used predominantly for heating	10	No	Yes
Car own.	Car ownership	Ownership of car or truck	57	No	Yes
Motorcycle own.	Motorcycle ownership	Ownership of motorcycle	50	No	Yes
Appliance own.	Appliance ownership	Ownership of refrigerator, washing machine, television or air conditioning	57	No	Yes

Table 1: Features and feature groups used to predict carbon intensity of consumption
This table shows features and corresponding feature groups that we use to predict carbon intensity of consumption. All sociodemographic features refer to self-identified information of individuals. Column 'Countries' refers to the number of countries with non-missing information for each feature. For some countries, we have removed some features for prediction because of unreasonably high (e.g., *District*) or no resolution (e.g., *Education*). See also Appendix A.3 for further information about features. Column 'Sparse' indicates whether we include each feature in our *sparse* model. Column 'Rich' indicates whether we include each feature in our *rich* model.

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 30 different combinations of learning rate, maximum depth of trees, and fraction of features contained in each tree[21]. For each country, we select the combination of

[21]We combine different values for learning rate ($\eta \in [0.001, 0.3]$), maximum depth of trees (`max_depth`

hyperparameters that minimizes the mean absolute error (MAE).

Based on our selected 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 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.

Logit model For supplementary robustness analyses, we fit a logit model to identify households whose consumption is substantially more carbon-intensive than the population as a whole. We construct a binary variable $e_i^{80^{th}}$ for each household i indicating whether the household is among the most carbon-intensive 20% of households in each country, i.e., in the top quintile of carbon intensity:

$$e_i^{80^{th}} = \begin{cases} 1, & \text{for } e_i \geq e^{80} \\ 0, & \text{for } e_i < e^{80} \end{cases} \tag{11}$$

With $P_{e_i^{80}}$ representing the probability that the consumption of household i is more carbon-intensive than 80% of the population in each country, we are interested in the coefficients β' of the following logit model:

$$log\left(\frac{P_{e_i^{80}}}{1 - P_{e_i^{80}}}\right) = \alpha_0 + \beta' X_i' + \varepsilon_i \tag{12}$$

Estimation of a logit model serves as a robustness check for results from BRT models. It also allows for the examination of characteristics associated with 'hardship case' households, including an accessible interpretation of results and parameters. For the purpose

$\in \{x \in \mathbb{N} \mid 3 \leq x \leq 15\}$), 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_latin_hypercube()` from the *tidymodels* package in R. We show the resulting and preferred combination of hyperparameters in Table C.8.

of meaningful comparison across countries, we present results from logit models using average marginal effects for each independent variable.

Identification of country clusters Country-level analyses can be useful to identify country-specific household characteristics that are associated with higher carbon intensity of consumption. To explore similarities and differences in the importance of characteristics across many countries, we seek to identify clusters of countries.

The relationship between household-level characteristics and carbon intensity of consumption is unique to each country, but also depends on the availability of granular data. We adjust for the importance of individual features by multiplying the importance of individual features and the country-level goodness of fit (R^2) to account for differences in available features across countries (see also Figure B.1.3). This approach also helps to account for the aggregate performance of country-level models and allows for the better comparison of feature importance across countries. Our resulting measure of feature importance thus accounts for the contribution of individual features to explaining *observed* values of carbon intensity rather than *predicted* values of carbon intensity.

Based on the (adjusted) feature importance for each country, we use the k-means algorithm for clustering. If features are missing in the data, we assume that their share of contribution is zero[22]. We normalize all feature values to allow for comparison between features. If a feature is more (less) important in one country compared to all other countries, the processed feature value will be relatively high (low). If a feature is equally important in all countries, the processed feature values will be close to zero. We also include vertical distribution coefficients $\widehat{V}_r$ for clustering because our measure of feature importance of household expenditures does not capture the *direction* of effects.

K-means clustering is an unsupervised machine learning method and helps to analyze clusters of observations that are most similar in many variables *within* each cluster and least similar in many variables *across* clusters (MacQueen 1967). We examine the optimal number of clusters ($\{k \in \mathbb{N} \mid 3 \leq k \leq 20\}$) using average silhouette widths (Rousseeuw 1987) for each cluster k. The silhouette width s_i expresses the average Euclidean distance of each observation i to all other observations within its cluster and for the average distance to observations from the nearest neighboring cluster. Silhouette widths closer to 1 indicate a good fit of an observation to its cluster, and silhouette widths closer to -1 indicate a poor fit. The average silhouette width $\overline{s_k}$ for each cluster k expresses how well all observations fit, on average, into each cluster. Our approach yields $k = 6$ as the number of clusters that maximizes the average silhouette width[23]. We also show the optimal number of clusters for k-means clustering based on unadjusted feature importance

[22]As a robustness check, we replace missing entries with the average values of all non-missing values. We use adjusted feature importance, i.e., we assume that the (imputed) contribution of unobserved features does not have a strong correlation with observed features.

[23]See Figures B.5.1 and B.5.2 for visualization.

($k = 5$) and on adjusted and imputed feature importance ($k = 9$) in the Appendix[24].

Within the same cluster, individual features are similarly important in predicting households' carbon intensity. For each cluster, we compute averages for each feature to allow us to examine differences between countries in different clusters.

It is important to note that our approach of adjusting feature importance by overall predictive performance reduces the bias introduced by the limited availability of some features in the data at hand. Uncorrected feature importance values can be exaggerated when few features are available, so countries with few features may end up in the wrong cluster, mainly because the BRT model cannot help explain much of the variation in carbon intensity. Instead, our approach ensures that all *observable* features contribute to clustering. Despite many structurally unobservable characteristics at the household level, our approach may be justified under the assumption that policy design can naturally focus only on observable household characteristics. This is particularly true for the design of compensation policies and when targeting errors are to be minimized.

3.4 Methodological limitations

While our approach can serve as a consistent method for studying heterogeneous impacts of climate policy, some methodological aspects are a limitation 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. 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.

Our approach allows for a consistent, harmonized analysis across countries, but falls short of accounting for the deployment of cleaner technologies since 2017. Yet, to our knowledge, more recent MRIO data with broad geographic coverage are not available.

[24]See Figures B.5.3, B.5.4, B.5.5, and B.5.6 for visualization. Using unadjusted feature importance for clustering changes the interpretation of clusters: Features of countries within the same cluster contribute similarly to explaining variation in carbon intensity, regardless of the availability of features in the data and the explanatory power of the model.

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[25].

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[26].

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 clustering of countries is subject to uncertainty and depends on the criteria used for clustering. Our approach of adjusting the importance of features helps to avoid that countries end up in a cluster simply because features are missing in the data. Nevertheless, if we had more information to observe or if we included different criteria, countries might end up in different clusters. Arguing that we include all relevant and available criteria while minimizing redundancy, clustering can be useful to identify similarities in divergence. As a robustness check, we impute missing values for feature importance with averages and show the resulting clusters in Figures B.8.3 and B.8.4.

4 Results: Determinants 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. We compare the importance of features across countries and assign countries to clusters accordingly.

[25] Including general equilibrium effects was found to lead to lower additional costs compared to short-term impacts (Ohlendorf et al. 2021).

[26] 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.

Vertical and horizontal distributional effects 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. Figure 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 44 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 all 20 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 18 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).

Figure 2 also shows that within-quintile heterogeneity in carbon intensity is greater in the poorest quintile than in the richest quintile ($\widehat{V}_r > 1$) 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 68 countries. 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 Figure 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 B.6 and Table C.16 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., Cosbey et al. 2019; Mehling et al. 2019), would lead to increasing heterogeneity among richer households relative to poorer households in 58 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 59 countries, while differences in horizontal heterogeneity exceed vertical differences in 79

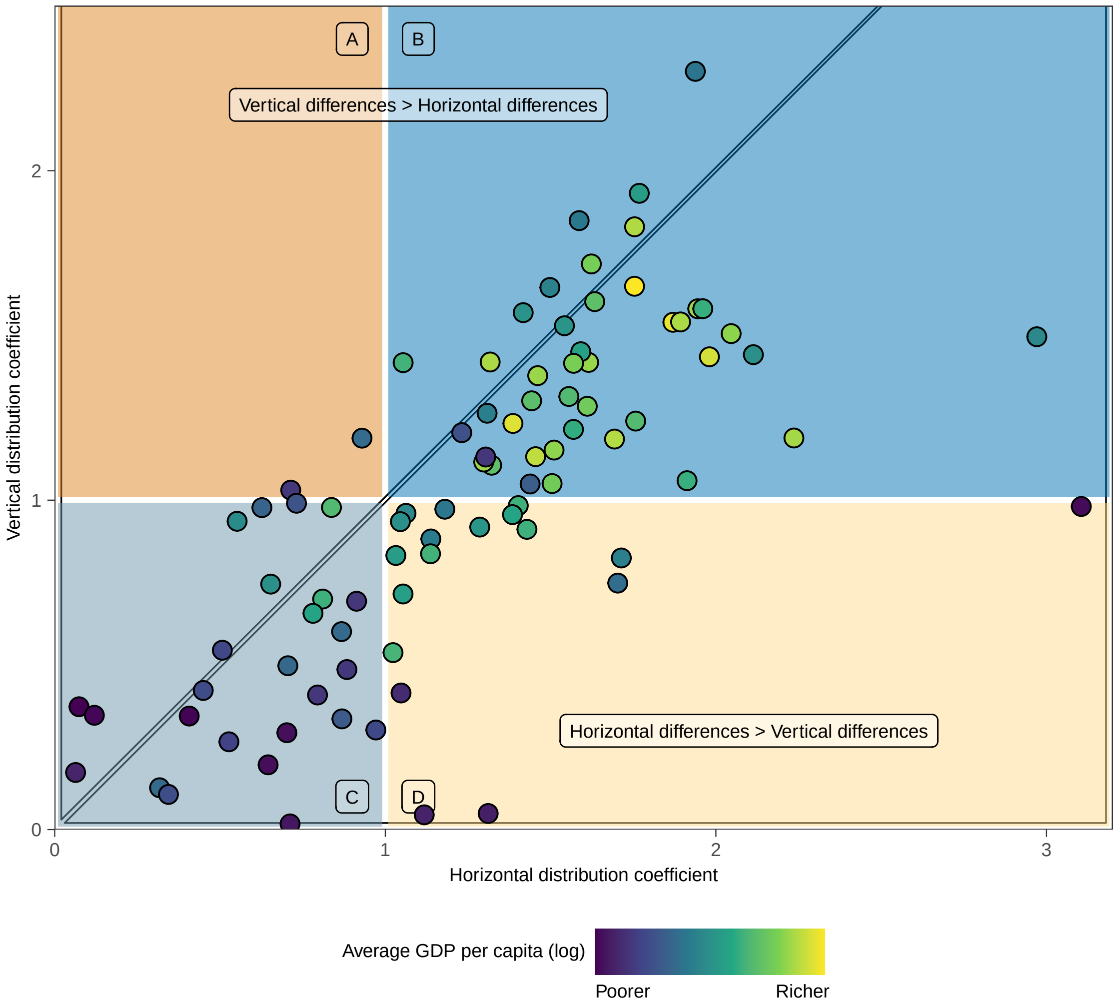


Figure 2: Vertical and horizontal distribution coefficients

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 (5^{th} to 95^{th} 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 C.9 lists both distribution coefficients for all countries and also shows an alternative measure for $\widehat{H_r}$, i.e., comparing the difference between the 20^{th} and 80^{th} within-quintile percentiles for the poorest and the richest quintiles.

countries. In contrast, electricity sector policies are likely to affect poorer households more in 62 countries, with greater horizontal heterogeneity among poorer households in 65 countries.

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 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[27]. 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 based on important features.

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 4% for *sparse* BRT models including only total household expenditures (see Figure B.7 or Table C.10). In 79 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 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 23% 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 59% (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, 53% for Peru, and 52% for Niger, and exceeds 30% in 27 countries (Table C.10).

For some countries, however, the accuracy of rich models is comparatively low. In 17 countries, R^2 does not exceed 10%. Model accuracy is lowest in Bulgaria (1%), Estonia, Hungary, and Suriname (3%). One reason is that model performance depends critically on data granularity. In cases of low 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 ($\widehat{V}_r^1 = 0.92$) and horizontal differences within expenditure quintiles are comparatively large ($\widehat{H}_r^1 = 1.29$, see also Figure B.4.2). 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

[27]Specifically, goodness of fit (R^2) has a convenient interpretation. Assume that governments would choose a set of transfers that, on average, equalizes relative additional costs. The goodness of fit then indicates the maximum possible reduction in horizontal heterogeneity in % compared to the policy impact without compensation.

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. Figure 3 and Table C.11 show the adjusted feature importance for all features in each country, our vertical distribution coefficient, mean CO_2 intensity, and R^2, grouped by country clusters[28]. 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 B.9).

Without adjusting for model accuracy, the most important feature across countries is total household expenditures, with a relative contribution of 22% on average. Household expenditures is the single most important feature for prediction in 33 countries, and in some countries, such as Luxembourg and Croatia, differences in household expenditures contribute more than 50% to model prediction. Adjusting for model accuracy, household expenditures contributes most to prediction in Peru (18%), Ecuador (14%), and Iraq (14%) – 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 52 countries, overall increasing for 13 countries, following an inverted U-shape for 11 countries and a U-shape for six countries (see Figure B.9). We find strictly decreasing relationships between household expenditures and carbon intensity for 17 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 15 and 13 countries, respectively. In Burkina Faso, Niger, 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 (32%) and Taiwan (18%). 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

[28]See Table C.12 and Figure B.8.2 for the unadjusted feature importance for all features in each country. See Table C.13 and Figure B.8.3 for the adjusted and imputed feature importance for all features in each country.

household are the most important feature in 15 countries. For example, differentiating between urban and rural households contributes more than 40% of the model prediction in countries such as Spain, the Czech Republic, and France. We find that urban households consume less carbon-intensively than rural households in 45 countries (such as Brazil, Germany, and Norway), and more carbon-intensively in 10 countries (such as Mongolia, Pakistan, and Romania). For Mongolia, where state of residence accounts for 9% of the adjusted feature importance, we document that households in Western Mongolia or Ulaanbaatar consume more carbon-intensively than households in Central Mongolia or the Highlands. In Jordan, where department of residence accounts for an adjusted feature importance of 5%, households in Al-Quesmah and Na'oor districts consume more carbon-intensively than households in other departments. 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 Romania, where the data lack features describing energy access and that could account for differences between urban and rural households.

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 seven of the countries where such features are available. Main cooking fuel is an important feature in Peru and Nicaragua, with an adjusted feature importance of 19% and 15%, 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. The use of kerosene for lighting is associated 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 9% for Rwanda. Information on heating fuels is available in only a few countries, but is the single most important feature in Turkey and Armenia. Here, carbon intensity is higher in households that heat with coal (Turkey) or natural gas (Armenia) than in households that heat with electricity. In other countries, such as the United Kingdom, Brazil, Austria, and Uruguay, the adjusted feature importance of heating fuels accumulates to no more than 3.5%.

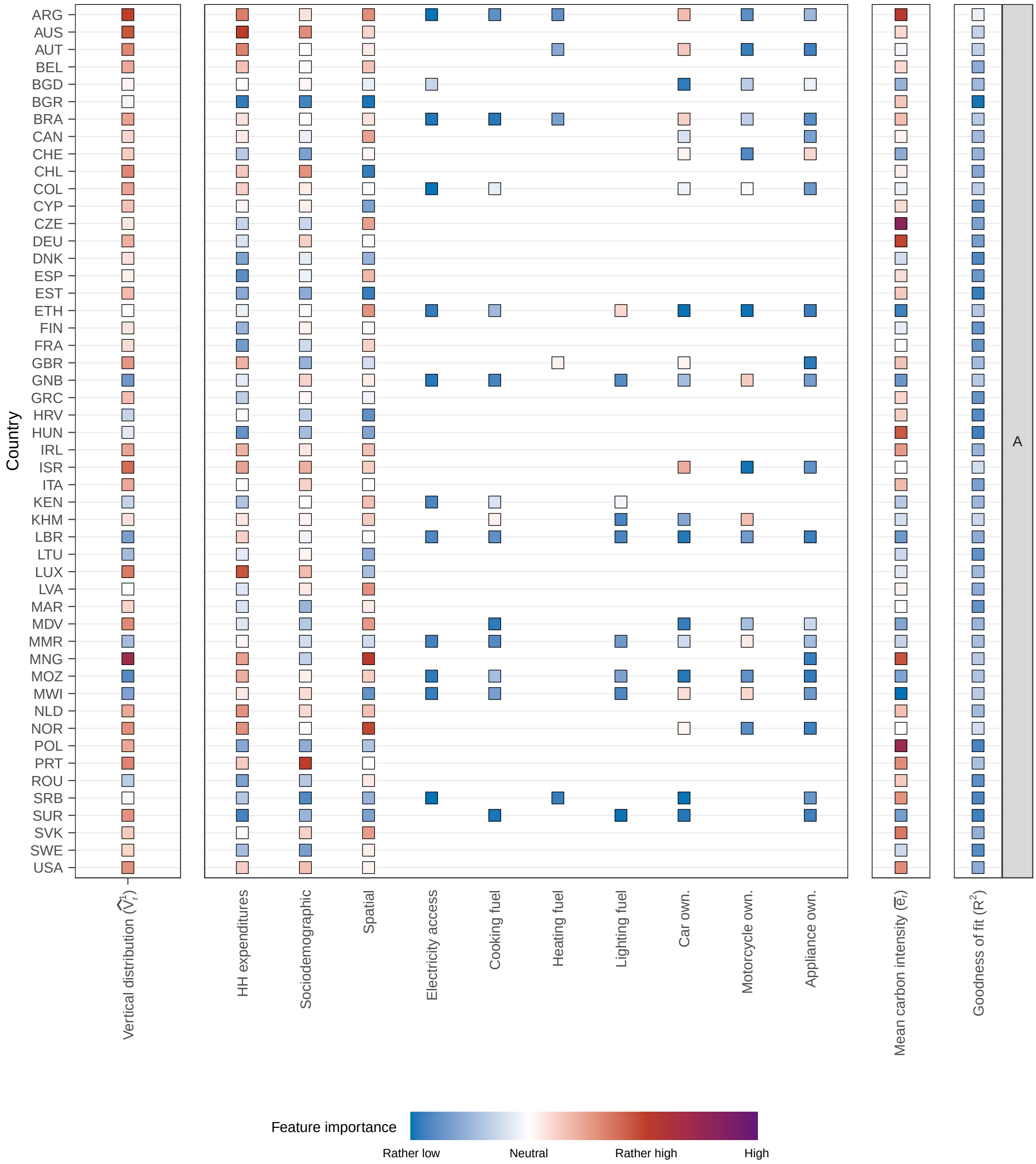
Overall, electricity access is less frequently an important feature, contributing a maximum of 4% of the adjusted feature importance in Senegal. In the majority of countries, the feature importance for electricity access is low, possibly because of overall high electricity access rates (e.g., Vietnam and the Philippines) or low electricity access rates (e.g., Malawi and Liberia, see Table C.2) or low carbon intensity of the electricity sector (e.g., Ethiopia and Kenya, see Table C.14).

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 compelling, but incomplete, proxy 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 feature in three countries. In Portugal, for example, where household education accounts for 28% 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 identify as Muslim are found to consume more carbon-intensively than households that identify as Jewish. Israeli 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 3% of the adjusted feature importance, indicating their relatively low relevance across countries for predicting differences in carbon intensity.

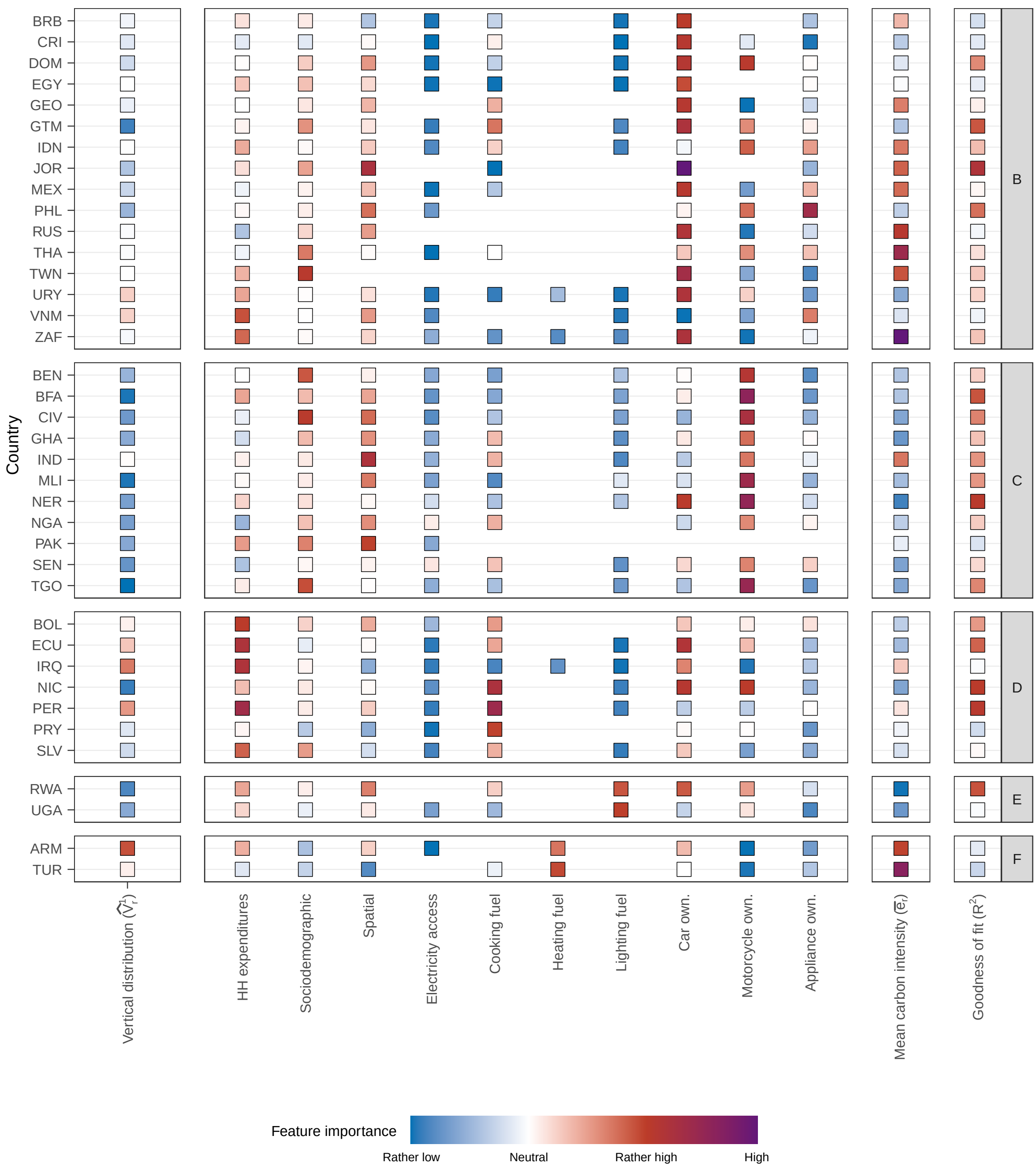
Figure 3: Feature importance across countries by cluster

(3.1) Feature importance across countries in Cluster A



This figure shows the importance of features (in normalized average absolute SHAP values) for each country, grouped by 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 goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity and R^2 are not explicitly used for clustering. We assign countries to six clusters using k-means clustering based on scaled feature importance, adjusted for model accuracy. We also report all values in Table C.11.

(3.2) Feature importance across countries in Clusters B to F



This figure shows the importance of features (in normalized average absolute SHAP values) for each country, grouped by country clusters. Blue (red) colors indicate that a feature is relatively less (more) important in a country than in 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 goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity and R^2 are not explicitly used for clustering. We assign countries to six clusters using k-means clustering based on scaled feature importance adjusted for model accuracy. We also report all values in Table C.11.

Identification of country clusters Countries are comparable 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 six distinct clusters of countries. Within clusters, countries are more similar to each other than to countries in other clusters.

It is worth noting that not all countries fit well into their clusters, as indicated by an average silhouette width of 0.29 (see Figures B.5.1 and B.5.2 and Tables C.11 and C.15). In Cluster B, for example, the silhouette width is negative for five countries, indicating greater heterogeneity between countries or, more generally, idiosyncratic patterns. Under such circumstances, it may be more difficult to draw conclusions about the distributional impacts of climate policy from the experiences of other countries.

Clusters differ in the importance of individual features. Figure 4 shows the relative importance of different features across clusters, after ordering the clusters by cluster size.

The largest cluster, Cluster A, comprises 50 countries (including the USA, Canada, Brazil, and Germany). In countries in this cluster, our analysis shows more carbon-intensive consumption among relatively poorer households. Compared to other clusters, most features contribute relatively little to explaining variation in carbon intensity. For example, the average adjusted feature importance is 3.5% for household expenditures, which is the most important feature across all 88 countries. More generally, countries in Cluster A have in common that it is difficult to predict households' carbon intensity with the available data. One reason is that we adjust the country-level feature importance for model performance, which influences the identification of country clusters. For example, 18 out of 18 countries with relatively low model performance (R^2<10%) appear in Cluster A. In particular, the data resolution may be insufficient and does not cover variables describing energy use (37 countries in this cluster lack information on main cooking fuels and 30 countries lack information on car ownership). Nevertheless, these results also point to highly idiosyncratic determinants of heterogeneous carbon intensity with important implications for policy design. This is because attempts to compensate on the basis of characteristics observable in our dataset (such as total household expenditures) will not be effective in compensating the households most affected by climate policy. This is also the case in countries where more granular information is available, such as Brazil, Colombia, Israel, Kenya, and the United Kingdom. Nevertheless, the impact of climate policy can be large, as evidenced by a comparably carbon-intensive consumption in countries such as Australia, the Czech Republic, Mongolia, and Poland.

Cluster B includes 16 countries (such as Indonesia, Mexico, the Philippines, and South Africa) with relatively high average carbon intensity (0.91 $kgCO_2$/USD on average). Within countries, differences in carbon intensity between poorer and richer households are relatively small, but richer households consume more carbon-intensively in all countries except Uruguay and Vietnam. Countries have in common that spatial information and appliance and car ownership are comparably important features. Compared to other clusters, countries are less similar to each other, expressed by an average silhouette width of -0.02.

Cluster C includes 11 countries (such as India, Nigeria, and Pakistan) with comparatively less carbon-intensive consumption (0.39 $kgCO_2$/USD on average). In countries in this cluster, the consumption of richer households is more carbon-intensive. Motorcycle ownership, spatial information, and sociodemographic characteristics are relatively more important than in other clusters, while the adjusted feature importance for household expenditures is 3.5%, on average. It is striking that nine countries in Cluster C are among the 22, i.e., the quarter of countries in our sample with the lowest GDP per capita. Nine out of 17 countries in sub-Saharan Africa belong to Cluster C, although this information was not used for clustering. Instead, the clusters indicate heterogeneous patterns of energy use. One implication is that it may be inaccurate to infer the distributional impacts of climate policy in one country from the experience of other countries, where patterns of energy use may be different.

Cluster D consists of six countries in Latin America (Bolivia, Ecuador, El Salvador, Nicaragua, Peru, and Paraguay) and Iraq. In this cluster, household expenditures, main cooking fuel, and car ownership stand out as important features compared to other clusters.

The countries in Cluster E (Rwanda and Uganda) differ from all other countries in that the variation in the main lighting fuel and spatial information is comparably relevant for predicting carbon intensity. In contrast, the main household heating fuel is a relatively important feature in the two countries in Cluster F (Armenia and Turkey). In addition, we observe that both clusters E and F include geographically neighboring countries[29].

While our clustering approach is inherently stylized, it helps to highlight country-specific characteristics that correlate with (and contribute to) heterogeneous impacts of climate policy on households. Importantly, we provide evidence that differences in household expenditures are less determinant of households' carbon intensity than is often assumed. Features describing household energy use may be helpful predictors in some countries (e.g., in Clusters B, C, D, E, and F), but not necessarily in all countries. For example, in countries in Cluster A such as Brazil, Argentina, and Ethiopia, where the predictive power of the models is relatively high, the main energy fuels contribute relatively little to the prediction.

Robustness check: Direction of effects Results from BRT models can help us to understand the contribution of each feature to the prediction of carbon intensity. Moreover, such model results also indicate the (non-linear) relationships between feature values and carbon intensity, as visualized in partial dependence plots (Figure B.9). Here, we build

[29] See also Figure B.11 for visualization.

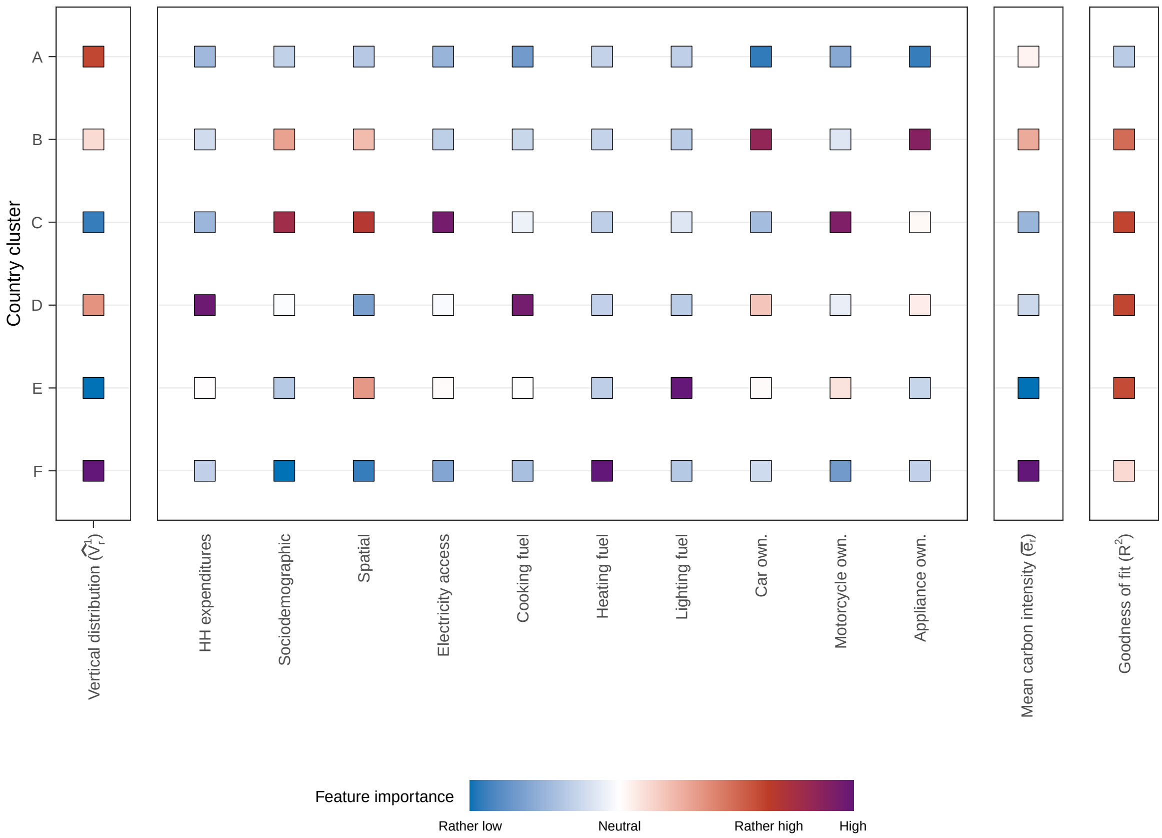


Figure 4: Average feature importance across country clusters

This figure shows the average importance of features (in normalized absolute average SHAP values) across all countries from each cluster A to F. Colors express the average importance of features in a cluster compared to other clusters. Blue (red) colors indicate that a feature is relatively less (more) important on average in a cluster compared to all other clusters. 'Sociodemographic' includes normalized absolute average SHAP values for features such as education, gender, self-identified ethnicity, nationality, religion, and language. 'Spatial' includes normalized absolute SHAP values for 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 clusters. For goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity and R^2 are not explicitly used for clustering. We assign countries to six clusters using k-means clustering. We also show all values in Table C.15.

on supplementary analyses based on a logit model (see Figure B.10 and Equation 11) to discuss and support our findings on the direction of the effects and to allow for a more accessible comparison across countries.

In the majority of countries, increasing expenditures is associated with a lower probability of being a hardship case: Estimates are less than and statistically different from zero ($p \leq 5\%$) for 62 countries (Figure B.10.1). The estimates are positive and significant ($p \leq 5\%$) for 11 countries. By comparison, our analysis of vertical heterogeneity (i.e., between-quintile differences, see Figure 2) yields progressive results in 44 countries. Thus, in some countries, poorer households may be more likely to consume more carbon-intensively than 80% of the population, even though the overall distribution is progressive, again supporting our claim that a focus on vertical heterogeneity can be misleading.

Across countries, we document that owning (and using) a car (Figure B.10.2) or motorcycle (Figure B.10.3) is associated with a significant increase in the probability of consuming more carbon-intensively than 80% of the population[30]. In 11 countries, our estimates show a significantly ($p \leq 5\%$) higher probability of being in the most carbon-intensive quintile for urban households, but a lower probability in 33 countries compared to rural households (Figure B.10.4).

While the findings from logit models are generally in line with our results from BRT models, each model answers a slightly different question. In particular, models with binary dependent variables can be useful for analyzing distributional impacts because they help describe how parts of the population (e.g., the most carbon-intensive quintile) differ from other parts of the population[31]. For example, for Mexico we find that differences in cooking fuel use account for 2% of the adjusted feature importance for predicting carbon intensity, but cooking with coal instead of electricity is associated with a 43% higher probability of consuming more carbon-intensively than 80% of the Mexican population. Under such circumstances, addressing the use of (specific) cooking fuels may be warranted, even though the adjusted feature importance is comparatively low.

Robustness check: Alternative clustering Our preferred approach to clustering may place undue weight on missing information about feature importance. It is evident that countries in Cluster A have in common that many variables remain unobserved, especially on energy use. To address this shortcoming, we identify country clusters after imputing missing information for feature importance by feature-level averages. Supplementary Figure B.8.3 and Table C.13 show the resulting clusters.

We identify nine alternative clusters. The largest cluster A^1 contains 42 countries, including 37 countries that are part of Cluster A. Twelve countries that we identified as part of Cluster A in our preferred analysis end up in the second largest cluster, Cluster B^1, which contains 17 countries. The main differences between A^1 and B^1 are the adjusted feature importance for household expenditures which is higher for countries in Cluster B^1 (8%) than in Cluster A^1 (3%), and goodness of fit (R^2, 13% and 23%, respectively).

Cluster C^1 includes countries where car ownership is an important predictor. Spatial information is similarly important in countries in Cluster D^1, and motorcycle ownership and sociodemographic characteristics are similarly important in countries in Cluster E^1. Identical to our main analysis, Rwanda and Uganda (Cluster F^1) and Armenia and

[30]The exception for car ownership is Ethiopia, where car ownership is associated with a *decrease* of 14% ($p = 0.046$) in the probability of being in the most carbon-intensive quintile. However, our BRT model yields an unadjusted feature importance of 0.1% for car ownership in Ethiopia. One reason for this is the comparatively small variation in car ownership in the Ethiopian data.

[31]Supervised machine learning models are also well suited for analyzing variation in a binary dependent variable, i.e., classification problems.

Turkey (Cluster H^1) end up in a cluster because of lighting and heating fuels, respectively. Nicaragua and Peru (Cluster G^1) stand out because of the importance of cooking fuels, while the Philippines is relatively different from all other countries because of appliance ownership, which is an important predictor.

Overall, this alternative approach to clustering emphasizes the illustrative purpose of our clustering exercise. Clustering appears to be comparatively sensitive to unobserved features. This supports our conclusion that prevailing idiosyncratic patterns determine households' carbon intensity of consumption[32]. In the search for effective compensation measures, governments may need to address both hidden information and structurally unobservable determinants that drive households' technology use.

5 Discussion: Unpacking the policy toolbox

Our findings provide evidence for country-specific household characteristics associated with higher carbon intensity of consumption. These results can be useful in ex-ante assessments of climate policy to identify particularly affected household profiles and thus promising policies to compensate them. Both the persistence of horizontal heterogeneity and the identification of different country clusters suggest that commonly proposed compensation options, such as uniform lump-sum transfers, may not be effective in compensating the most carbon-intensive households in the context of each country. Moreover, most of the discourse on complementary compensation policies focuses on industrialized countries belonging to Cluster A, where, as we show, household characteristics associated with carbon-intensive consumption may differ substantially from countries in other clusters. For example, poorer households consume more carbon-intensively than richer households, and the observed heterogeneity in carbon intensity is difficult to predict, as indicated by an average goodness of fit of 13%.

We refrain from proposing specific compensation policies for particular countries, and recognize that preferences for one measure over the other may be subject to many normative considerations at the government level, as described in Chapter 2. Admittedly, compensation becomes more feasible when climate policy builds on price-based interventions, such as carbon pricing or fossil fuel subsidy removal, thereby increasing the fiscal space to reimburse households. Moreover, a thorough comparison of alternative compensation policies should take into account existing institutions, potentially constrained government capacity, and the limited information available to policymakers. With these limitations in mind, we examine which options in the policy toolbox could be more effective in supporting those households that would bear the highest additional costs, thereby reducing horizontal heterogeneity[33].

[32]For example, the average silhouette width decreases to 0.22 for our alternative clustering approach.

[33]Our analysis can also shed light on *existing* compensation policies for climate policy. Austria, for

Uniform lump-sum transfers, potentially distributed equally per capita, are the poster child of many economists. Indeed, such transfers would be applicable if governments had a strong preference for reducing vertical inequality while avoiding regressive effects[34] and ensuring high salience of compensation (Chetty et al. 2009). In contrast, research draws attention to the relatively low public acceptance of such transfers and the 'equity-pollution-dilemma'[35] (Sager 2019).

Our analysis shows that 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. Such transfers could be comparatively effective in reducing horizontal heterogeneity in countries in Cluster D, including Bolivia, Ecuador, El Salvador, Iraq, Nicaragua, and Peru.

Many governments have established *cash transfer programs targeting low-income households*. Leveraging such existing institutions could be beneficial, even though targeting errors of cash transfer programs can be substantial (Banerjee et al. 2022) and associated with lower public acceptability (Bah et al. 2019). Our results suggest that transfers targeting low-income households may be helpful where poorer households consume more carbon-intensively than richer households and where household expenditures are not an important feature. In our sample, this is the case for some Cluster A countries such as the Maldives, Poland, and Suriname.

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example, introduced a carbon price in 2022. Revenues are distributed back to the population as a lump-sum transfer. However, the size of the transfer varies across regions, with higher transfers in regions with less transport and health infrastructure (BMK 2023). Our analysis for Austria shows that total household expenditures and spatial features account on average for 36% and 18% of the predicted values (R^2=0.21). Despite some remaining degree of unobserved heterogeneity and the lack of explicit differentiation of transfers with respect to primary heating fuels and car ownership, the compensation measures proposed by the Austrian government are likely to reduce horizontal heterogeneity.

In contrast, Canada introduced a nationwide carbon tax in 2019, with the proceeds going back to households through quarterly tax returns. Canadian households from rural regions receive an additional 10% of the transfers to account for higher dependence on fossil fuels for transportation (Government of Canada 2023). In 2023, the Canadian government announced that it would exempt heating oil from carbon pricing for three years to reduce additional costs for poorer households in the Atlantic provinces, which are more likely to use oil for heating (Reuters 2023). Our analysis for Canada shows that Canadian provinces account for 39% of the predicted values (R^2=0.16), but that households from the Atlantic provinces are less likely to consume carbon-intensively than households from Saskatchewan and Ontario. Exempting heating oil from carbon pricing may be effective in reducing costs for carbon-intensively consuming households if heating fuels not included in our sample contribute substantially to unexplained heterogeneity. Nevertheless, our analysis shows that Canadian provinces appear to be a poor proxy for heating fuels, suggesting that households from the Atlantic provinces may perceive the carbon tax suspension as less relief than the government may have expected.

[34] 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.

[35] Hypothetically, reimbursing households in proportion to their costs would minimize the distributional effects on aggregate, although it would partially offset the demand-side effects of the policy instrument because households would use (part of) their reimbursement to consume more carbon-intensive products (see also Stiglitz 2019).

The discipline has also popularized *reducing distortionary taxes* to reap a 'double dividend' (Bovenberg and Goulder 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 be an effective offset. Indeed, in some Cluster C countries, such as Pakistan and Burkina Faso, reducing labor taxes may be useful for effective compensation while also promoting formalization (Rocha et al. 2018; Jessen and Kluve 2021) and economic activity (Ulyssea 2018).

Beyond the benefits for aggregate efficiency, *reducing excise taxes on consumption* may be effective in countries where poorer households consume more carbon-intensively and where total expenditures are an important feature, e.g., in Cluster D countries. In addition, differentiated tax reductions (e.g., through VAT) could shift consumption towards less carbon-intensive products (Klenert et al. 2023). Reducing excise taxes on basic consumer goods, including food and some forms of energy, may reduce vertical heterogeneity because poorer households spend a larger share of their expenditure share on such goods in most contexts[36].

Uniform lump-sum transfers and (income or consumption) tax cuts would likely fall short of compensating the most carbon-intensive households in countries with large horizontal heterogeneity and low predictive power for total household expenditures. In such circumstances, it may be important to *enable access to low-carbon technologies.* This can help reduce the 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, for example through incentives for energy efficiency improvements, improved public transport systems, or investments in green mobility infrastructure. Such policies may be helpful in Cluster B countries such as Mexico and Costa Rica. The main cooking fuel is an important feature in some Cluster B and D countries. Here, subsidies for clean cookstoves or 'transition fuels' (such as LPG) may be effective. Exempting kerosene from regulation may be useful in Rwanda and Uganda (Cluster E), while addressing the heating sector through improvements in buildings may be helpful in Armenia and Turkey (Cluster F), where the main heating fuel is an important predictor.

An important concern for effective compensation arises from the low model accuracy found for some countries. 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 horizontal heterogeneity. In some countries, particularly in Cluster A, households' carbon intensity is difficult to predict, underscoring the importance of additional country- and policy-specific research, especially when governments face in-

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

formation problems (Mirrlees 1971). In this case, reducing excise taxes on comparatively carbon-intensive goods could contain increasing heterogeneity while preserving incentives for supply-side abatement (Goulder and Parry 2008).

Addressing the distributional 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 greater horizontal heterogeneity in general. In contrast, electricity sector policies would lead to more regressive effects with greater heterogeneity among poorer households. While we refrain from investigating the importance of household characteristics in predicting the outcomes of such policies for now, 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 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. Clustering countries according to how the costs of climate policy are distributed across the population 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 affects 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. 2023), at least compared to the literature quantifying distributional impacts.

6 Conclusion

This study is the first to provide a detailed analysis of the heterogeneous impacts of climate policy on households across a large number of 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 used supervised machine learning to identify household characteristics that help explain 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. Rather, horizontal heterogeneity outweighs vertical heterogeneity, and models based on household expenditures are comparatively less accurate. 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 quantified the contribution of individual features and showed that their relative importance varies compared to other countries. Using k-means clustering, we identified six country clusters with comparable distributional characteristics.

Our results 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. 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 identified 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 politically acceptable climate change mitigation.

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Appendix

Distributional impacts of climate policy and effective compensation: Evidence from 88 countries

A Data cleaning

We describe our approach to collecting, cleaning, and harmonizing microdata, and to feature engineering for machine learning analyses.

A.1 Collecting household data

We collect household budget survey data and extract several information before cleaning and harmonizing. Household budget survey data are often publicly available, but sometimes subject to a considerable fee. Table C.1 provides publishing organizations, names of surveys, and links to datasets used in this study.

- For each household, we include sociodemographic information about household members where available. In all survey, households are represented through 'household heads', i.e., persons that often contribute the largest share of household income or are responsible for purchase decisions. We use information on the 'household head' as a proxy for the entire household and collect information on education, gender, self-identified ethnicity, nationality, or religion of the 'household head'. We standardize information on education by using the International Standard Classification of Education (ISCED) to facilitate comparison across countries.
- We include spatial information where available, for example identifier for sub-national areas (provinces or states), sub-sub-national areas (districts) or villages. Often, surveys include an indicator for whether households live in urban or rural areas. Definitions of *urban* and *rural* may not be consistent across countries, but are certainly consistent within countries.
- We include information on energy use, such as on primary fuels used for cooking, lighting, and heating. We harmonize information on fuels across countries to account for different names and levels of detail across countries. For example, cooking fuels include charcoal, coal, electricity, firewood, gas, kerosene, liquid fuel, LPG, other biomass, or unknown fuels.
- We capture information on electricity access and create a binary variable that indicates if households have access to electricity through electricity grids, through generators, or solar panels.
- We collect information about ownership of major transport vehicles (such as cars, motorcycles, and trucks) and major household appliances (such as refrigerators, air conditioners, washing machines, and television). For each country, we only include information about ownership, but not about the precise number of owned vehicles and appliances. This helps improve consistency across countries.
- We collect all available information on household-level expenditures, integrating information from household-level and individual-level diary entries. We do not include

consumption information from home production, received as gifts, or as remuneration for labor. Our rationale is that it would be difficult for a climate policy instrument to cover self-produced goods and services that are not purchased on markets. We include all expenditures at the item level and extrapolate expenditures to yearly values. Often, households track expenditures over the course of a few weeks, but provide details on less frequent purchases in the past months or year. For more frequently purchased items, mostly food, this approach neglects seasonal consumption patterns, but resulting bias should be sufficiently small, since households are surveyed throughout the year.

- We do not include imputed expenditures, for example, for hypothetical rental payments, since including them would inaccurately overestimate total household expenditures and bias expenditure shares towards less carbon-intensive services.

Code written for each country-level dataset can be found in a stable online repository (see Appendix D.2).

A.2 Cleaning and harmonizing household data

Building on collected microdata from household budget surveys we perform several cleaning steps in order to harmonize datasets across countries as far as possible. Conditional on country-level data availability, we ensure that we clean all available data consistently.

- We remove households from the sample with missing information for key variables such as household size, sampling weights, or total expenditures.
- We code and treat missing information about other variables as missing or 'unknown' and remove variables for each country, if missing information are dominant.
- For each country, we address outliers of household expenditures at the item level. We consider any observation an outlier if it is in the 99^{th} percentile of all non-zero expenditures. We replace this observation with item-level median expenditures, thereby assuming that expenditure shares on such items are non-zero, but absolute values might have been exaggerated because of misreporting.
- We remove observations, if expenditures are negative, for example, because households sell items.
- We remove duplicates from our sample. We check separately for duplicates at the level of household information and at the level of expenditures on individual consumption items: We consider households spending the same amount of money on the same items duplicates.
- We remove all households from our sample if aggregate expenditures exceed mean aggregate expenditures by five standard deviations ($z > 5$).
- We use inflation rates from IMF (2020) and exchange rates from the World Bank (2023) to convert all local currencies to USD for the year 2017. Expenditures from

surveys conducted before 2017 are inflated; expenditures from surveys after 2017 are deflated. This ensures consistency with calculated sectoral CO_2 intensities as they refer to the year 2017. This approach does however neglect that expenditure shares may change with rising incomes and inflation. Adjustment for purchasing power parity (PPP) is not necessary because we refrain from comparing households across countries.

- We create matching tables to assign country-level expenditure items to 65 aggregate sectors and to four broad expenditure categories (energy, food, goods, services). Items, that are difficult to match to a specific sector or to a specific category, for example, 'other expenses', are matched to artificial sectors and categories labeled 'other'. Admittedly, we assume a carbon intensity of zero for such items in absence of more detailed information, but expenditure shares are generally low (0.7% on average across country-level averages).
- We delete observations for items indicating aggregate categories if this would lead to double-counting of single expenditures. We delete observations for items indicating taxes (e.g., 'property tax'), since including them would prove inaccurate to calculating expenditure shares and because items indicating tax payments are not available in each country.
- We match items pertaining to fuels such as firewood, charcoal, and other biomass to the sector *lumber* to account for indirect emissions attributable to production, transportation, and retail of these goods. However, we treat direct CO_2 emissions of such fuels as zero, in line with assumptions by the IPCC (Grad and Weitz 2023), but also because direct emissions of such fuels are often difficult to regulate.
- We also identify items indicating energy use and create separate variables listing expenditures for different energy items such as electricity, gasoline, diesel, kerosene, LPG, natural gas, charcoal, hard coal, firewood, and other biomass. All matching tables are available through a separate stable online repository (see Appendix D.2).

This procedure helps ensuring that sectoral expenditure shares are comparable across countries, even though not all surveys include information on the same number and detail of consumption items. We proceed with assigning households to expenditure quintiles based on total household expenditures per capita to account for differing expenditure shares in larger households. We use expenditure quintiles for our analyses in figures 1 and B.4.

Tables C.2, C.3, C.7, C.4, C.5 and C.6 show summary statistics for our final harmonized dataset, grouped by country and by country and expenditure quintile in Tables C.3 and C.7.

A.3 Feature engineering

Based on our harmonized dataset, we perform feature engineering on our variables (features) with the R-package `recipes` before performing analyses with BRT.

- We exclude any feature with missing variation (for four countries).
- We exclude categorical feature with extremely high granularity (such as district-level identifiers) or no granularity (such as education, in some cases).
- We exclude any feature with missing values.
- We remove the minimum number of features necessary to avoid high levels of correlation ($r > 0.9$) between all features.
- We code observations as 'other' for each feature (except province-level, district-level and urban/rural identifiers) that account for less than 5% of all observations.
- All country-level feature sets include total household expenditures (in USD 2017) and household size. The minimum number of included features (including binary, categorical, and continuous features) is 4 (for Sweden) and the maximum number of included features is 17 (for Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Senegal, and Togo).

A.4 Policy simulation

We show that heterogeneity in the carbon intensity of consumption at the household level is equivalent to heterogeneity in household-level costs of climate policy, assuming that such instruments increase marginal costs of emitting CO_2 and that producers pass on such costs to consumers. This analysis thus disregards general-equilibrium-effects on both the supply- and the demand-side. In general, any climate policy instrument is conceivable in this exercise that leads to increasing costs in equivalence to embedded direct and indirect emissions, including (but not limited to) carbon pricing, fossil fuel subsidy removal, or subsidies for low-carbon fuels.

The carbon intensity of consumption e_i consists of sectoral carbon intensities and household-level sectoral expenditure shares as shown in Equation 5.

For example, consider the case of carbon pricing, which can be thought as a tax τ in USD/tCO_2. The total absolute costs from carbon pricing equals direct and indirect carbon emissions embedded in household consumption E_i multiplied with τ. Computing total relative costs c_i requires division by total household expenditures C_i:

$$c_i = \frac{E_i * \tau}{C_i} \tag{13}$$

Relative additional costs, i.e., the carbon pricing incidence c_i can be expressed in %, i.e., the fraction of absolute additional costs (USD_τ) over total household expenditures (USD_i). c_i is equivalent to our expression for carbon intensity of consumption e_i, scaled by a proportional factor τ. If $e_A = 2 * e_B$, then $c_A = 2 * c_B$, assuming that e_A and e_B express the carbon intensity covering all nationally released CO_2 emissions for households A and B and that c_A and c_B refer to the relative carbon pricing incidence for a carbon price levied on all nationally released emissions in households A and B, respectively. In essence, heterogeneity in carbon intensity is equivalent to heterogeneity in household-level costs of climate policy instruments, under assumptions about how such instruments affect the marginal costs of emitting CO_2.

In general, our modeling framework also allows for the simulation of other (sectoral) policies. Consider a carbon-tax-equivalent policy intervention in a specific sector, for example, in the transport sector, here denoted as τ_{s^*}. Such a sector-specific tax would cover all direct and indirect emissions released in this sector s^*, but not emissions released in other sectors. Nevertheless, customer prices of goods and services from sectors other than transport would still increase because of embedded emissions from the transport sector.

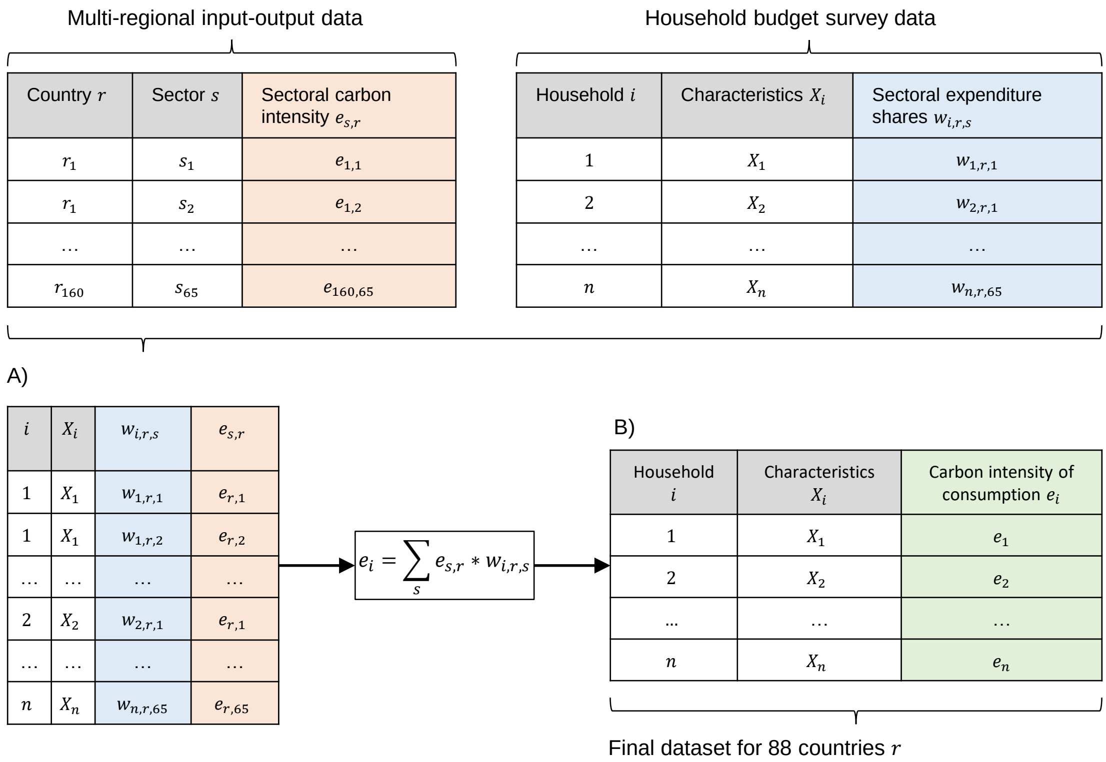
Calculating additional sets of sectoral carbon intensities e_{s^*} including direct and indirect emissions of different sectors can help simulate the impact of sectoral policies. Effectively, we only include direct and indirect CO_2 emissions released in sectors s^*.

It is also possible to analyze the distribution of regional policies, for example of carbon border taxes covering CO_2 emissions for imported goods and services.

Supplementary Figure B.6 shows vertical and horizontal distribution coefficients for the national carbon intensity in all sectors, in the transport sector, in the electricity sector and for the international carbon intensity in all sectors. See also Table C.16.

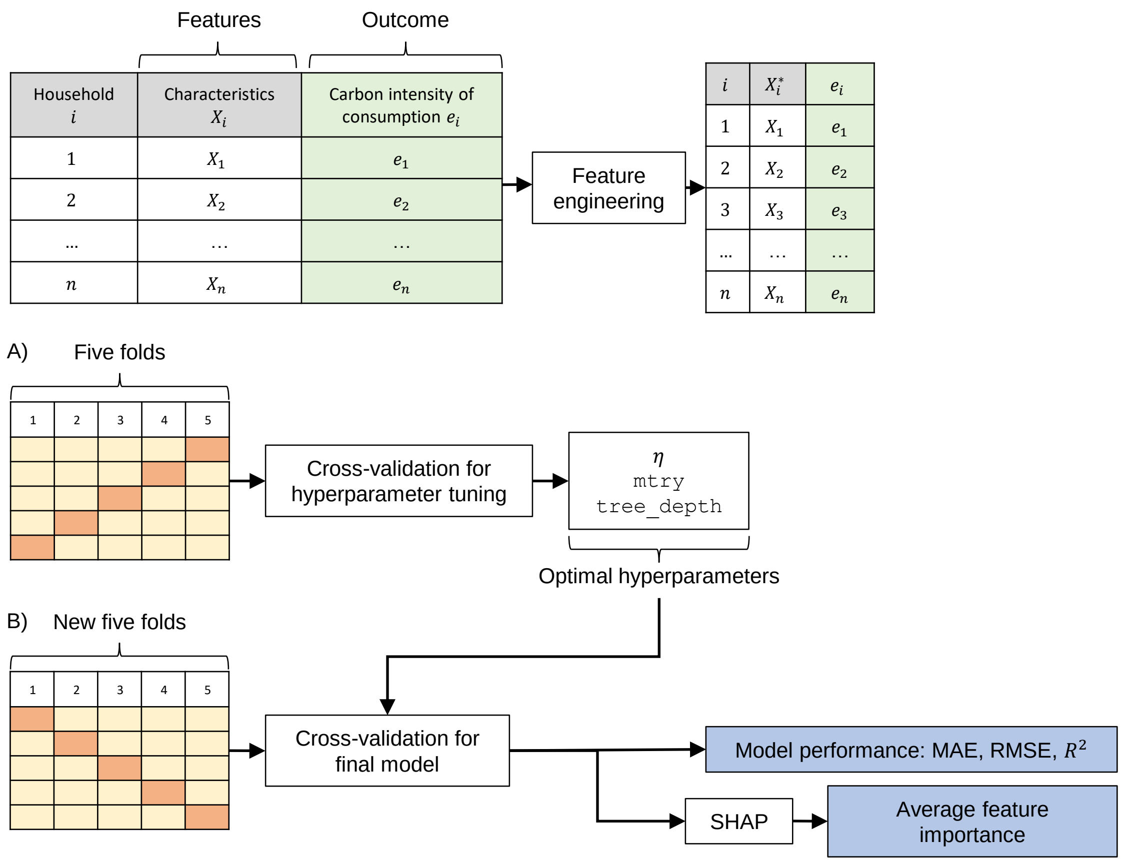
B Supplementary figures

Figure B.1: Graphical representation of data work



(B.1.1) Combination of household-level data and multi-regional input-output data

This figure shows the main properties of combining household-level data and multi-regional input-output data to calculate household-level carbon intensities of consumption e_i. Inputs are datasets with country-sector-level information about (direct and indirect) carbon intensities of output and datasets with household-level information about household characteristics and sectoral expenditure shares. Output is a dataset (B) with household-level information about household characteristics and carbon intensities of consumption e_i for 88 countries.



(B.1.2) Feature engineering, hyperparameter tuning, and model evaluation

This figure shows the main properties of feature engineering, hyperparameter tuning, and model evaluation. Input is a dataset with household-level information about household characteristics and carbon intensities of consumption e_i for 88 countries. Household characteristics form a set of features. After feature engineering, we use fivefold cross-validation for hyperparameter tuning. Building on optimal hyperparameters, we use fivefold cross-validation for our final model. Output is a vector of model performance indicators (MAE, RMSE, R^2) and a measure of average feature importance for each country and feature, based on SHAP-values.

Country r	Feature X^A with $A \in \{1,\dots,A'\}$	Average feature importance $\alpha_{A,r}$	Goodness of fit R^2_r	Adjusted feature importance $\alpha^*_{A,r}$
r_1	X^1	$\alpha_{1,1}$	R^2_1	$\alpha^*_{1,1}$
r_1	X^2	$\alpha_{2,1}$	R^2_1	$\alpha^*_{2,1}$
…	…	…	…	…
r_2	X^1	$\alpha_{1,2}$	R^2_2	$\alpha^*_{1,2}$
…	…	…	…	…
r_{88}	$X^{A'}$	$\alpha_{A',88}$	R^2_{88}	$\alpha^*_{A',88}$

Adjustment: Multiplication

A)

Country r	$\alpha^*_{1,r}$	$\alpha^*_{2,r}$	…	$\alpha^*_{A',r}$	$\hat{V}^1_r$	$\hat{H}^1_r$	$\bar{e}_r$
r_1	$\alpha^*_{1,1}$	$\alpha^*_{2,1}$	…	$\alpha^*_{A',1}$	$\hat{V}^1_1$	$\hat{H}^1_1$	$\bar{e}_1$
r_2	$\alpha^*_{1,2}$	$\alpha^*_{2,2}$	…	$\alpha^*_{A',2}$	$\hat{V}^1_2$	$\hat{H}^1_2$	$\bar{e}_2$
…	…	…	…	…	…	…	…
r_{88}	$\alpha^*_{1,88}$	$\alpha^*_{2,88}$	…	$\alpha^*_{A',88}$	$\hat{V}^1_{88}$	$\hat{H}^1_3$	$\bar{e}_{88}$

k-means clustering

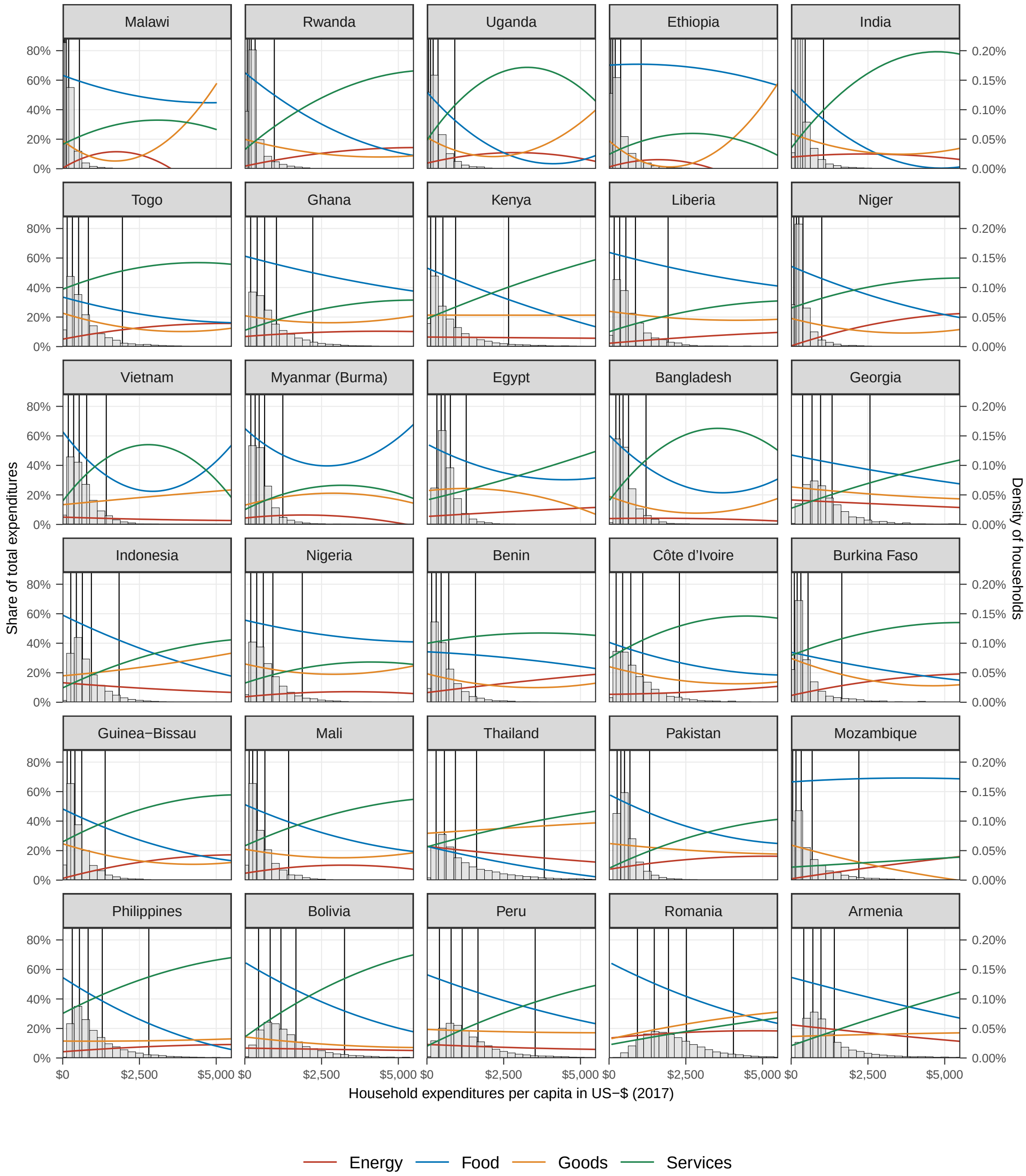
B)

Cluster k	$\overline{\alpha^*_{1,k}}$	…	$\overline{\bar{e}_k}$
k_1	$\overline{\alpha^*_{1,1}}$	…	$\overline{\bar{e}_1}$
k_2	$\overline{\alpha^*_{1,2}}$	…	$\overline{\bar{e}_2}$
…	…	…	…
$k_{k'}$	$\overline{\alpha^*_{1,k'}}$	…	$\overline{\bar{e}_{k'}}$

(B.1.3) Identification of country clusters

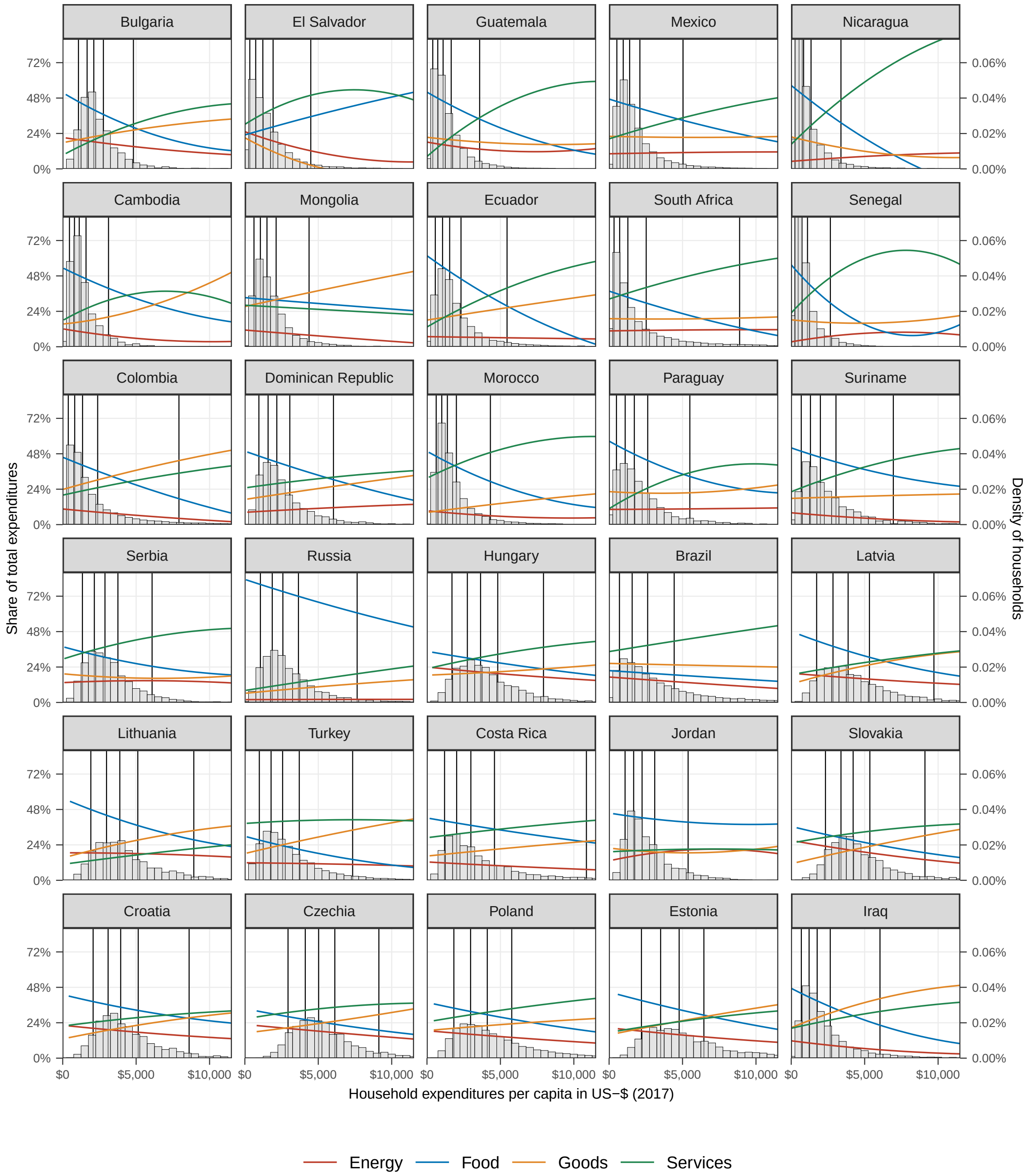
This figure shows the main properties of identifying country clusters. Input is a dataset with country-level information about average feature importance for each feature and models' goodness of fit (R^2). After adjusting feature importance, we use k-means clustering to identify a set of *k'* clusters. We use average silhouette width for selection of the optimal number of clusters *k'*. Output is a dataset with cluster-level information about average feature importance.

Figure B.2: Engel curves: expenditure shares over total household expenditures



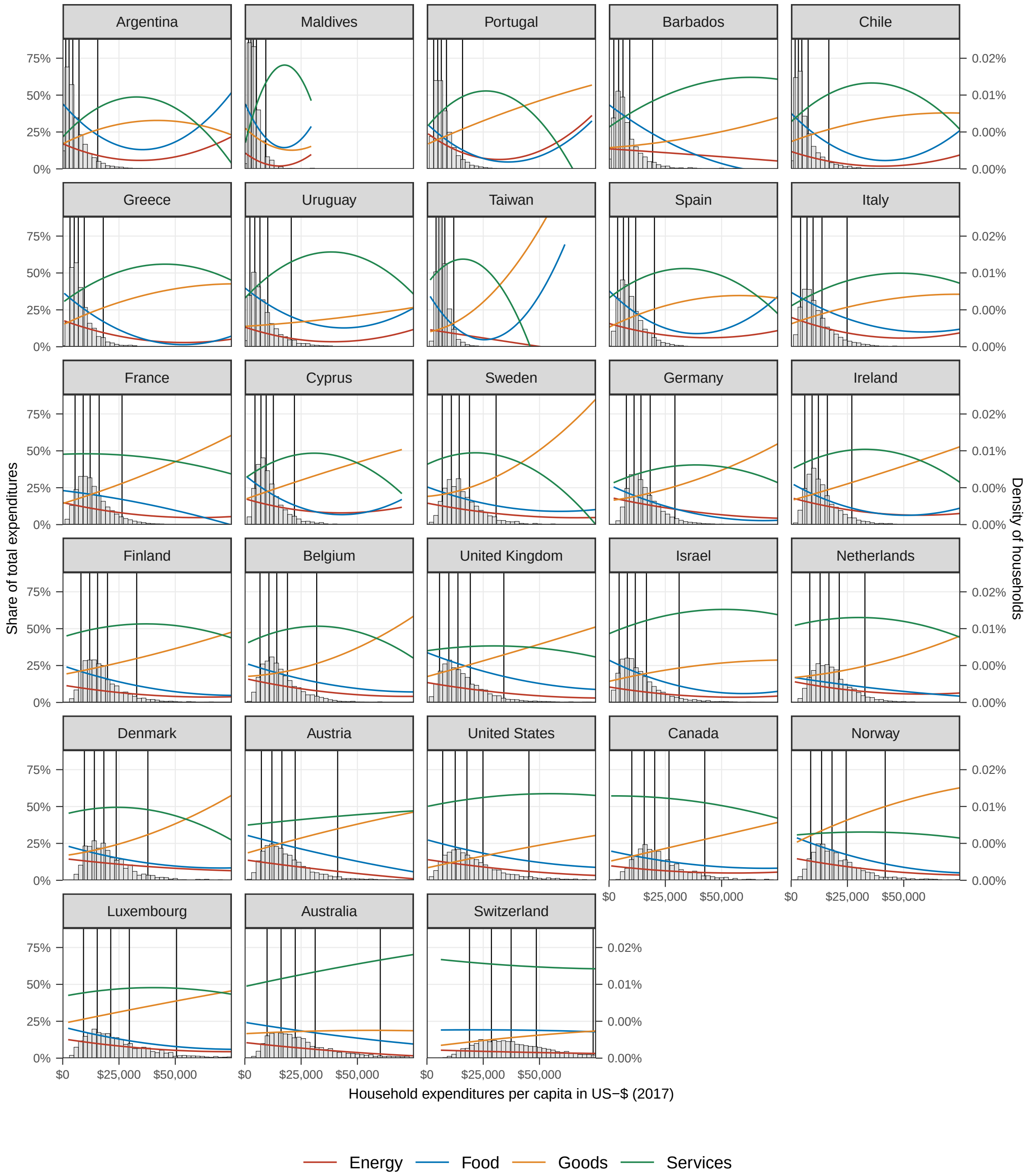
(B.2.1) Engel curves: expenditure shares over total household expenditures - Part A

This figure shows fitted lines for parametric and quadratic Engel curves for each consumption category in 30 countries of our sample. Black vertical lines indicate average household expenditures per capita for each expenditure quintile and country. Grey bars and secondary y-axis indicate the distribution of households.



(B.2.2) Engel curves: expenditure shares over total household expenditures - Part B

This figure shows fitted lines for parametric and quadratic Engel curves for each consumption category in 30 countries of our sample. Black vertical lines indicate average household expenditures per capita for each expenditure quintile and country. Grey bars and secondary y-axis indicate the distribution of households.



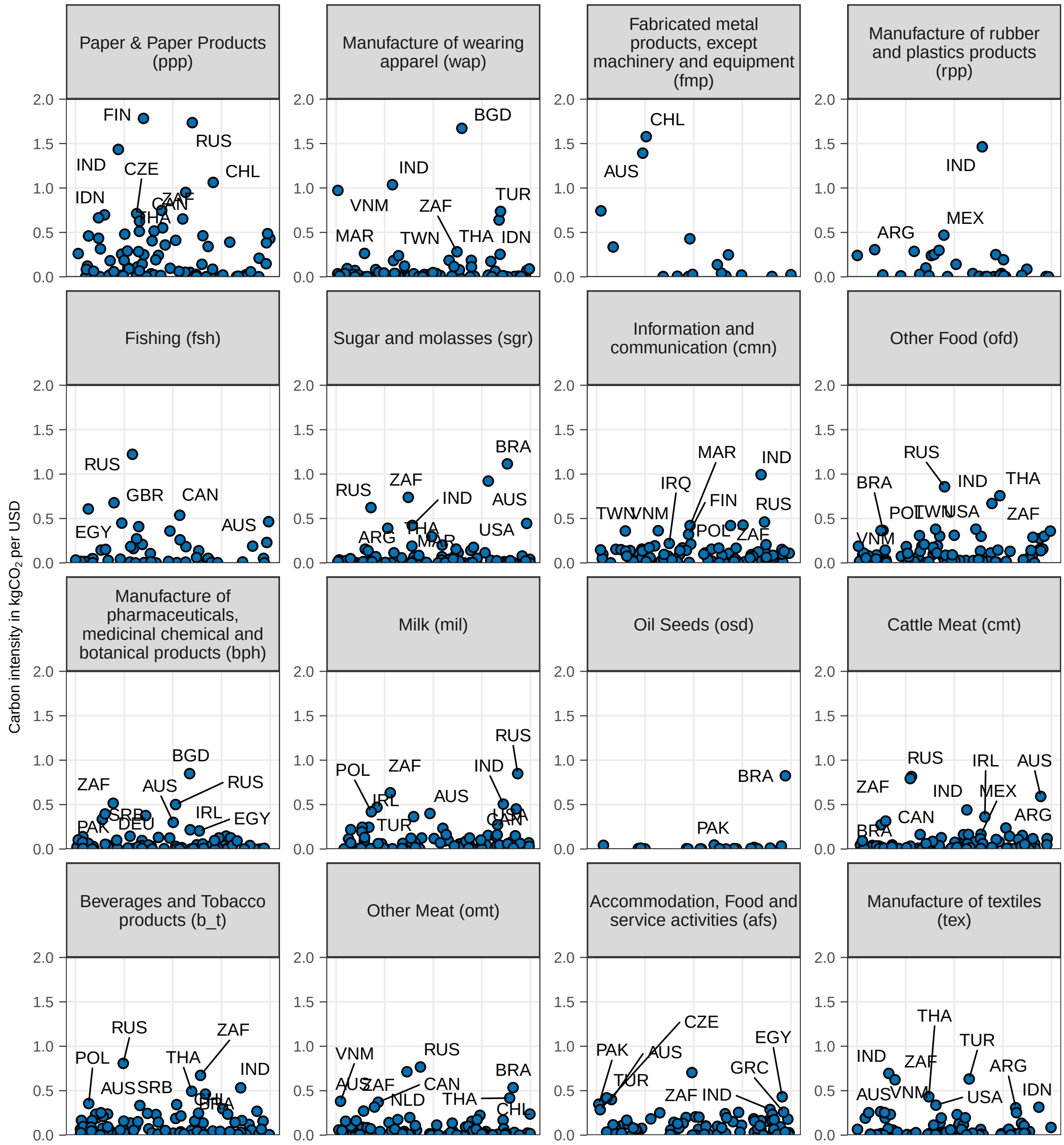
(B.2.3) Engel curves: expenditure shares over total household expenditures - Part C

This figure shows fitted lines for parametric and quadratic Engel curves for each consumption category in 27 countries of our sample. Black vertical lines indicate average household expenditures per capita for each expenditure quintile and country. Grey bars and secondary y-axis indicate the distribution of households.

Figure B.3: Sectoral carbon intensities from GTAP

(B.3.1) Sectoral carbon intensities from GTAP - Part A

This figure shows sectoral carbon intensities in $kgCO_2$ per USD of output for 16 sectors. We plot sectoral carbon intensities if household budget surveys in respective countries include consumption items that correspond to each sector. See our online repository for all country- and sector-level carbon intensities. We include labels with country codes if sector outputs are relatively carbon-intensive compared to other countries. Note that sectors *other mining extraction (oxt)*, *construction (cns)*, and *extraction of crude petroleum (oil)* are not matched to any item in any country.

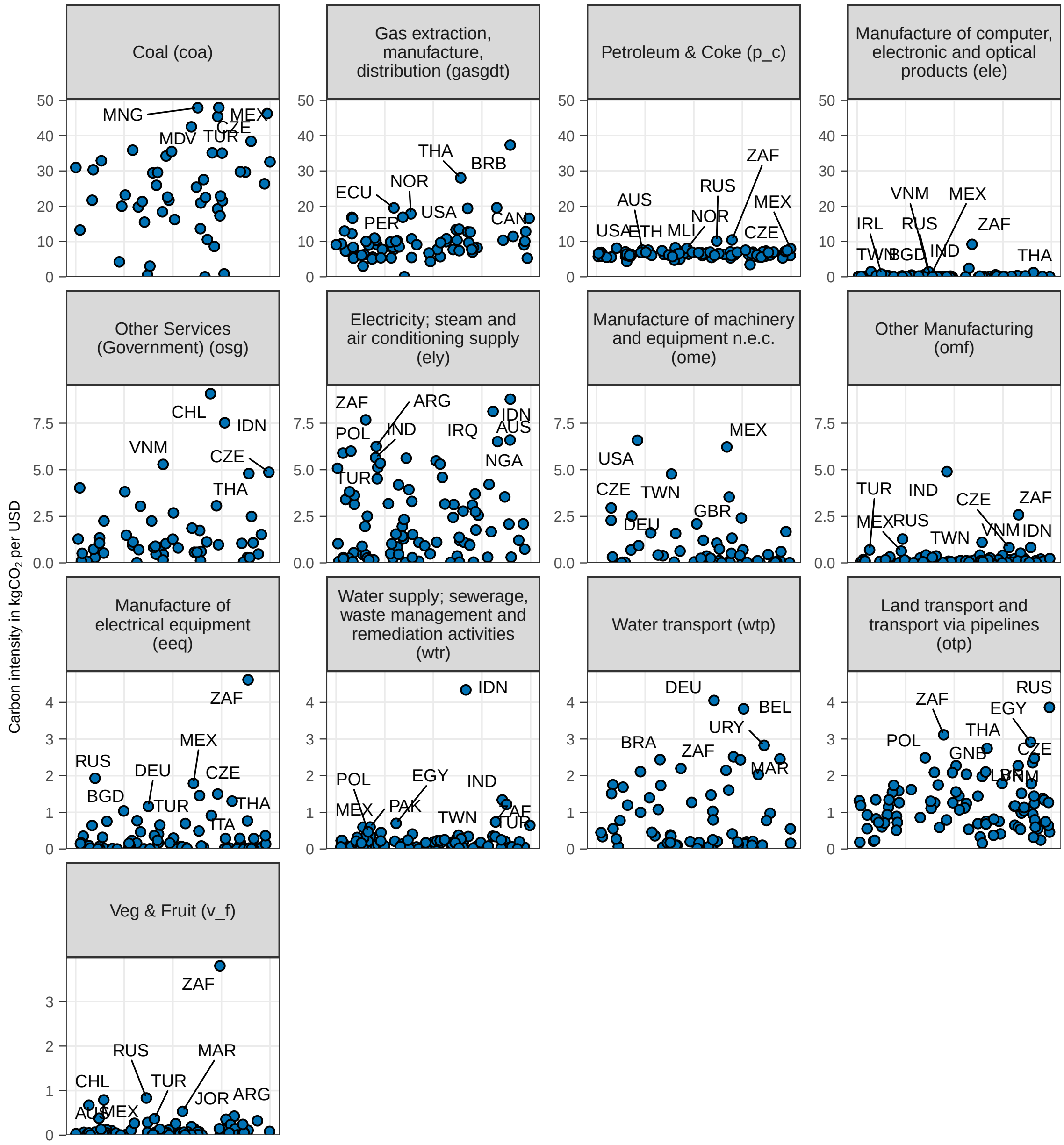


(B.3.2) Sectoral carbon intensities from GTAP - Part B

This figure shows sectoral carbon intensities in $kgCO_2$ per USD of output for 16 sectors. We plot sectoral carbon intensities if household budget surveys in respective countries include consumption items that correspond to each sector. See our online repository for all country- and sector-level carbon intensities. We include labels with country codes if sector outputs are relatively carbon-intensive compared to other countries. Note that sectors *other mining extraction (oxt)*, *construction (cns)*, and *extraction of crude petroleum (oil)* are not matched to any item in any country.

(B.3.3) Sectoral carbon intensities from GTAP - Part C

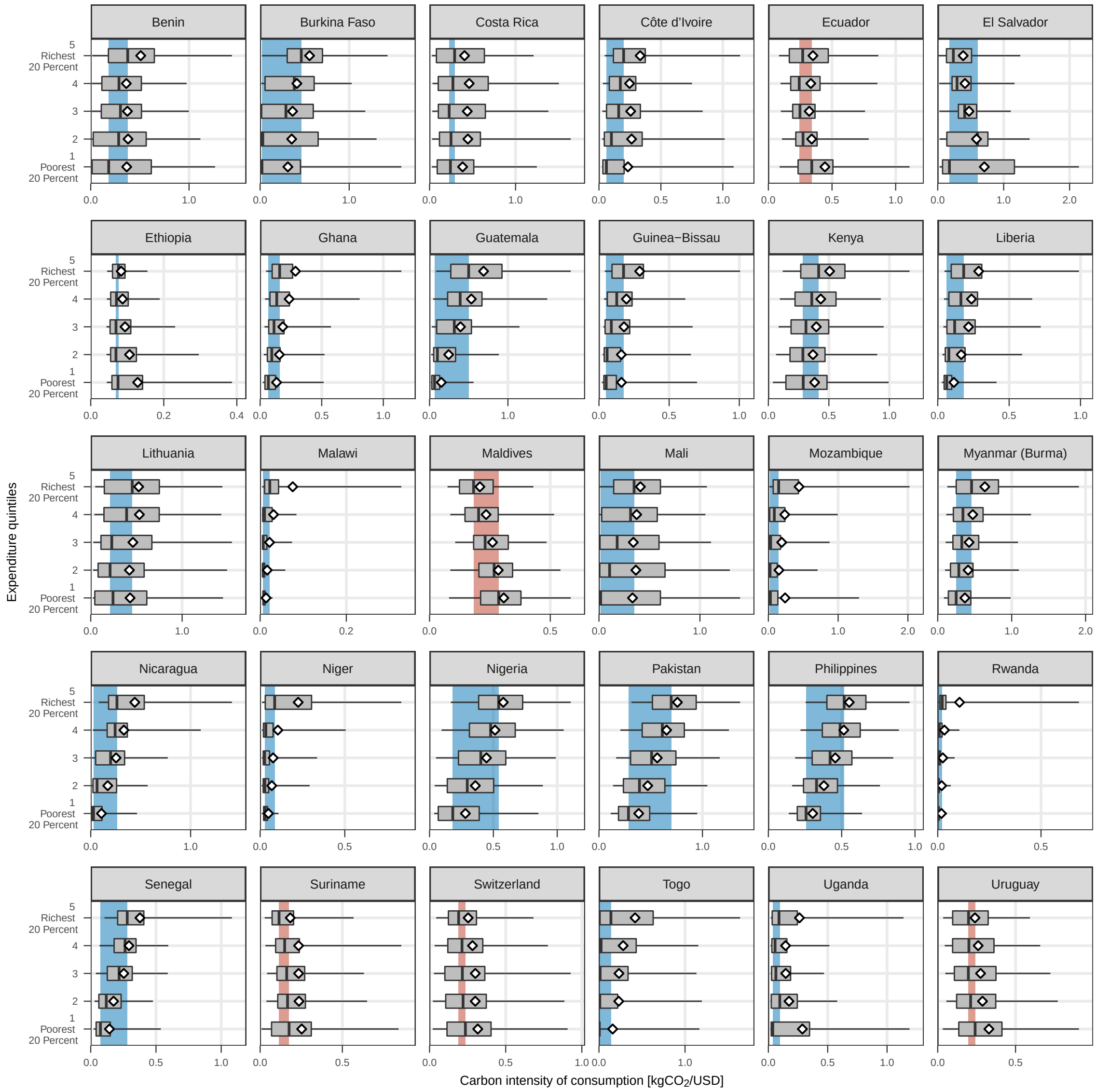
This figure shows sectoral carbon intensities in $kgCO_2$ per USD of output for 16 sectors. We plot sectoral carbon intensities if household budget surveys in respective countries include consumption items that correspond to each sector. See our online repository for all country- and sector-level carbon intensities. We include labels with country codes if sector outputs are relatively carbon-intensive compared to other countries. Note that sectors *other mining extraction (oxt)*, *construction (cns)*, and *extraction of crude petroleum (oil)* are not matched to any item in any country.



(B.3.4) Sectoral carbon intensities from GTAP - Part D

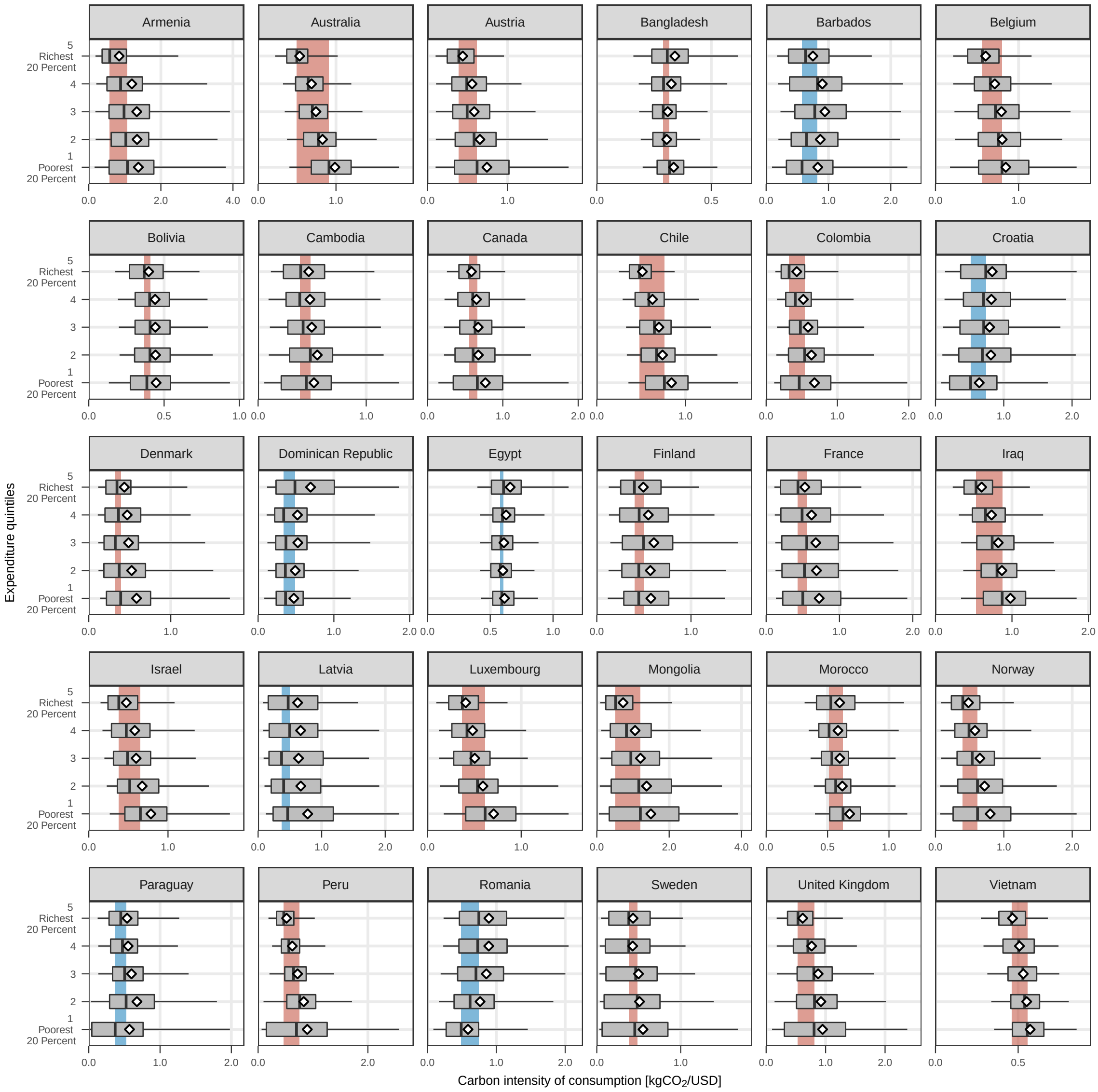
This figure shows sectoral carbon intensities in $kgCO_2$ per USD of output for 13 sectors. We plot sectoral carbon intensities if household budget surveys in respective countries include consumption items that correspond to each sector. See our online repository for all country- and sector-level carbon intensities. We include labels with country codes if sector outputs are relatively carbon-intensive compared to other countries. Note that sectors *other mining extraction (oxt)*, *construction (cns)*, and *extraction of crude petroleum (oil)* are not matched to any item in any country.

Figure B.4: Distribution of carbon intensities over expenditure quintiles



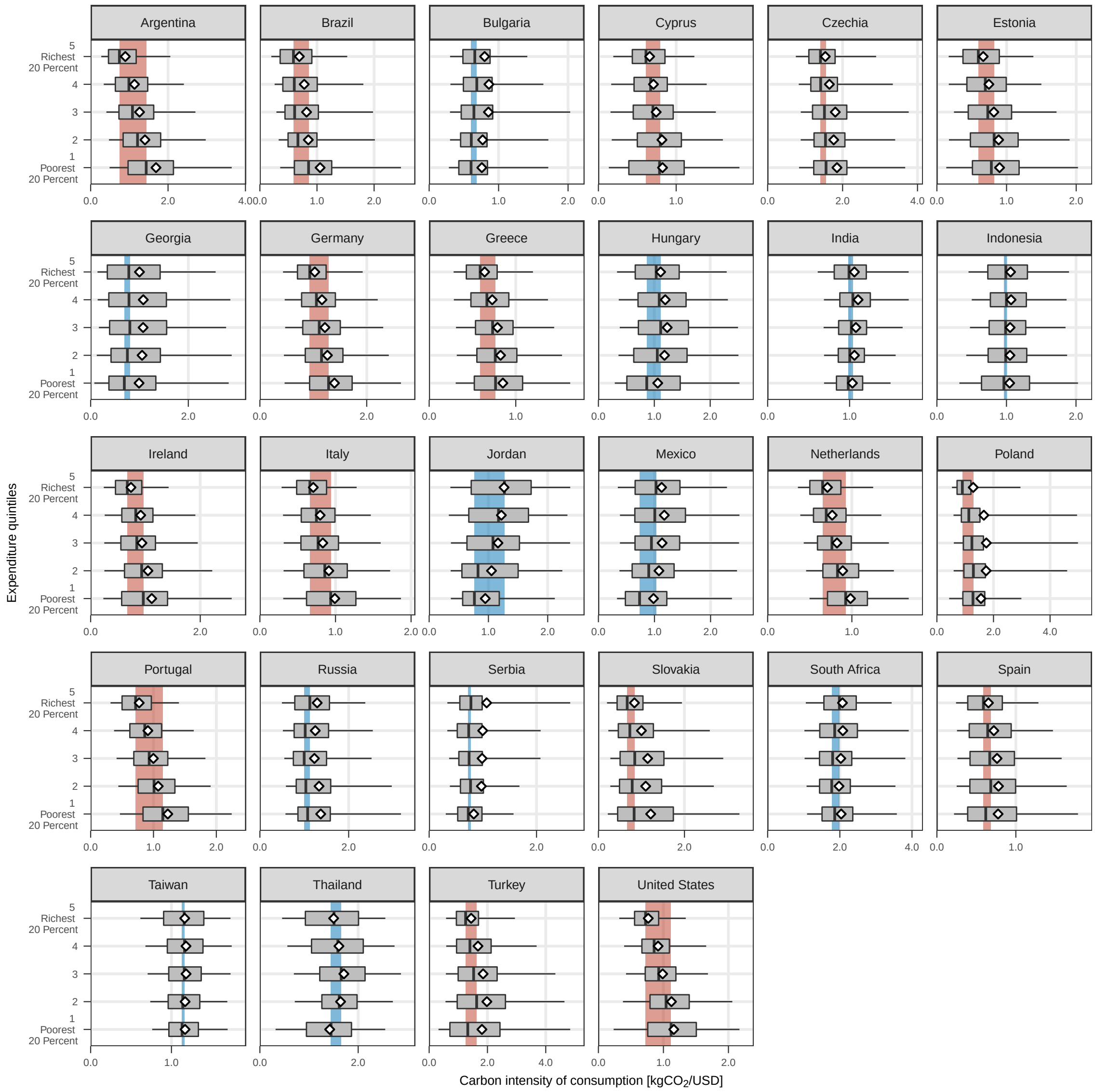
(B.4.1) Distribution of carbon intensities over expenditure quintiles - Part A

This figure shows the distribution of carbon intensity of consumption in kgCO_2/USD (x-axis) over expenditure quintiles (y-axis) for 30 countries. The first expenditure quintile comprises those 20% of all households with least total expenditures per capita. The fifth expenditure quintile comprises those 20% of all households with largest expenditures per capita. Within quintiles, boxes display the 25th and the 75th percentile; whiskers display the 5th and 95th percentile; rhombuses indicate the within-quintile average. Vertical colored bands indicate the difference between the highest and the lowest quintile-level median carbon intensity of consumption. Blue bands indicate higher carbon intensities among richer households; red bands indicate higher carbon intensities among poorer households. See also Tables C.7 and C.9.



(B.4.2) Distribution of carbon intensities over expenditure quintiles - Part B

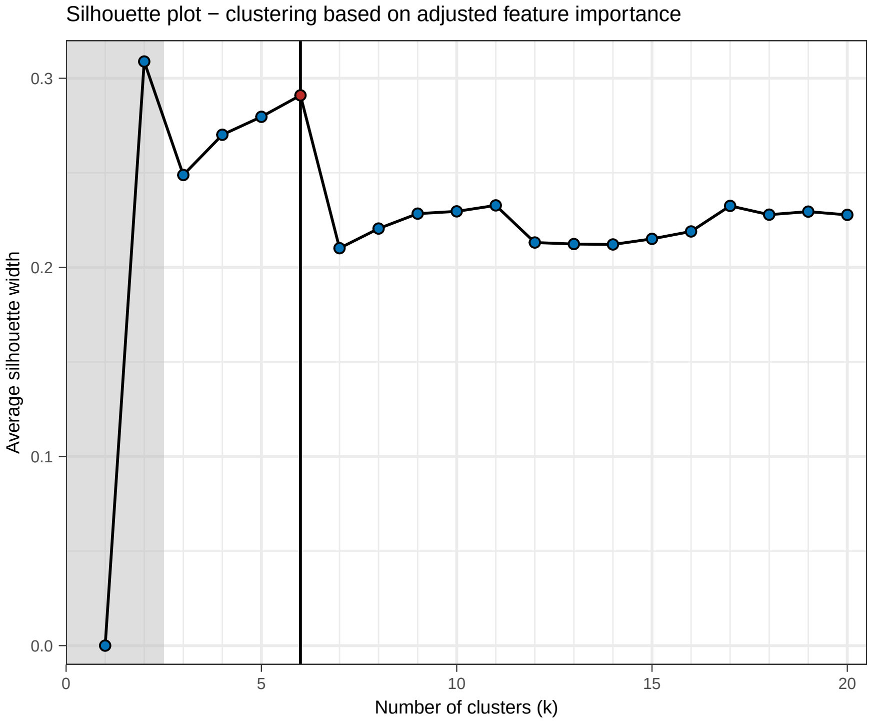
This figure shows the distribution of carbon intensity of consumption in $kgCO_2$/USD (x-axis) over expenditure quintiles (y-axis) for 30 countries. The first expenditure quintile comprises those 20% of all households with least total expenditures per capita. The fifth expenditure quintile comprises those 20% of all households with largest expenditures per capita. Within quintiles, boxes display the 25^{th} and the 75^{th} percentile; whiskers display the 5^{th} and 95^{th} percentile; rhombuses indicate the within-quintile average. Vertical colored bands indicate the difference between the highest and the lowest quintile-level median carbon intensity of consumption. Blue bands indicate higher carbon intensities among richer households; red bands indicate higher carbon intensities among poorer households. See also Tables C.7 and C.9.



(B.4.3) Distribution of carbon intensities over expenditure quintiles - Part C

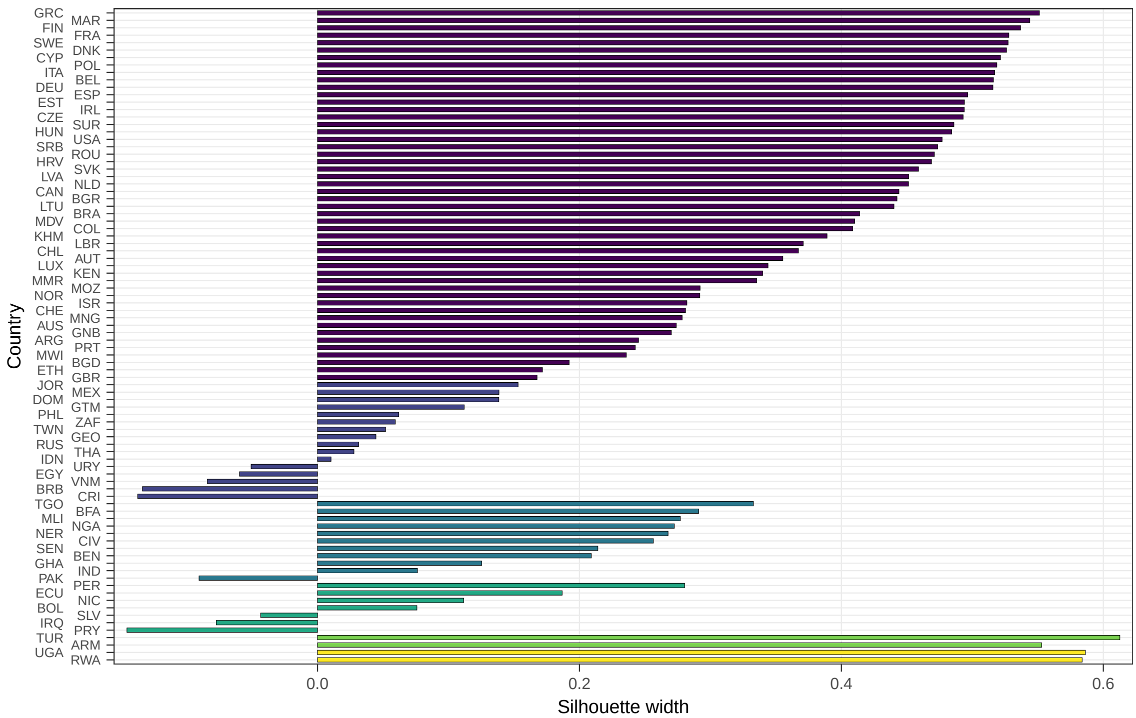
This figure shows the distribution of carbon intensity of consumption in $kgCO_2/USD$ (x-axis) over expenditure quintiles (y-axis) for 27 countries. The first expenditure quintile comprises those 20% of all households with least total expenditures per capita. The fifth expenditure quintile comprises those 20% of all households with largest expenditures per capita. Within quintiles, boxes display the 25^{th} and the 75^{th} percentile; whiskers display the 5^{th} and 95^{th} percentile; rhombuses indicate the within-quintile average. Vertical colored bands indicate the difference between the highest and the lowest quintile-level median carbon intensity of consumption. Blue bands indicate higher carbon intensities among richer households; red bands indicate higher carbon intensities among poorer households. See also Tables C.7 and C.9.

Figure B.5: Silhouette analysis



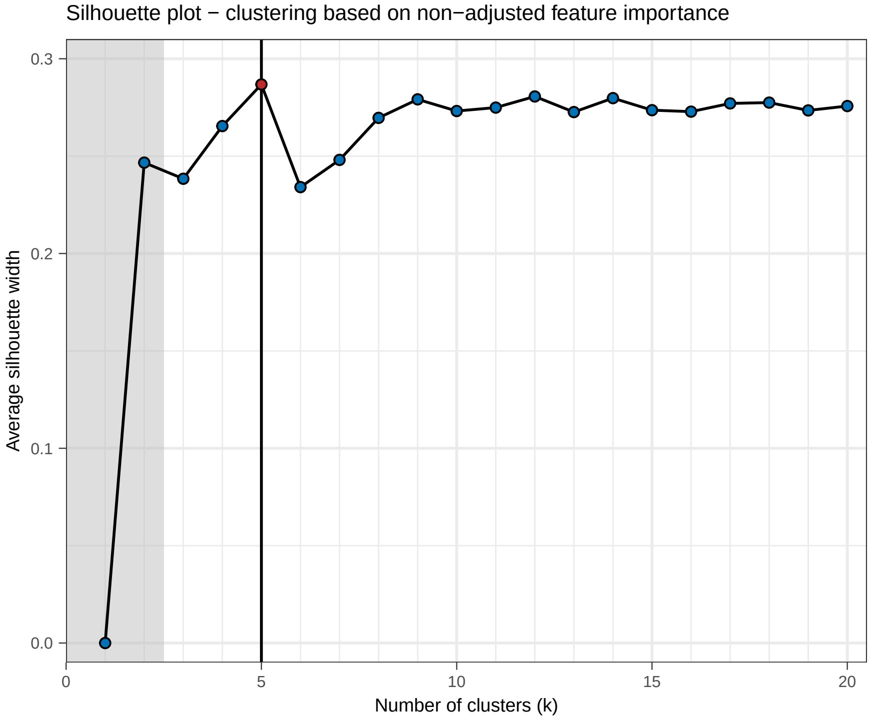
(B.5.1) Average silhouette width for different numbers of clusters k

This figure shows the average silhouette width across all clusters for different numbers of clusters k. We perform k-means clustering on a dataset with 88 observations at the country level. Observations include information on *adjusted* feature importance, i.e., we adjust feature importance for country-level model performance. We also include information about the vertical distribution. Vertical line and red point indicate the number of clusters that maximizes average silhouette width across all number of clusters with $k \geq 3$.



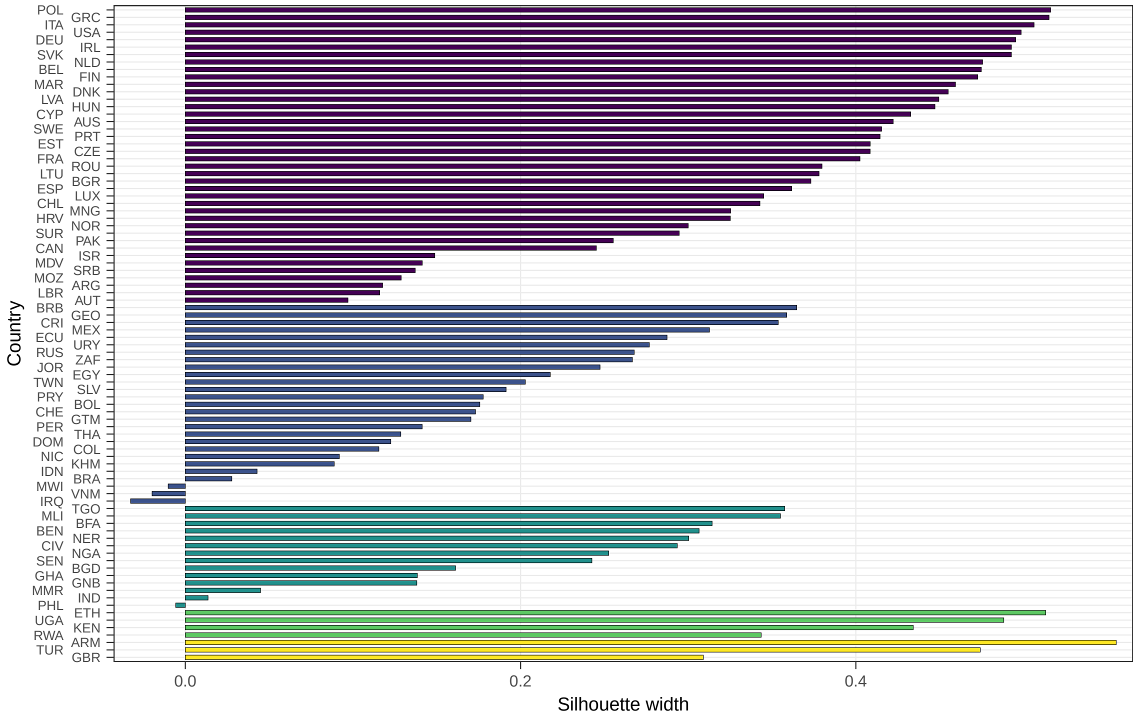
(B.5.2) Average silhouette width for each country per cluster k

This figure shows the silhouette for each country for six clusters. We perform k-means clustering on a dataset with 88 observations at the country level. Observations include information on *adjusted* feature importance, i.e., we adjust feature importance for country-level model performance. We also include information about the vertical distribution. We order observations (y-axis) by clusters with most observations and by silhouette width. Silhouette width expresses how well each observation fits in its cluster, also in comparison to the observations from the least distant, but different cluster.



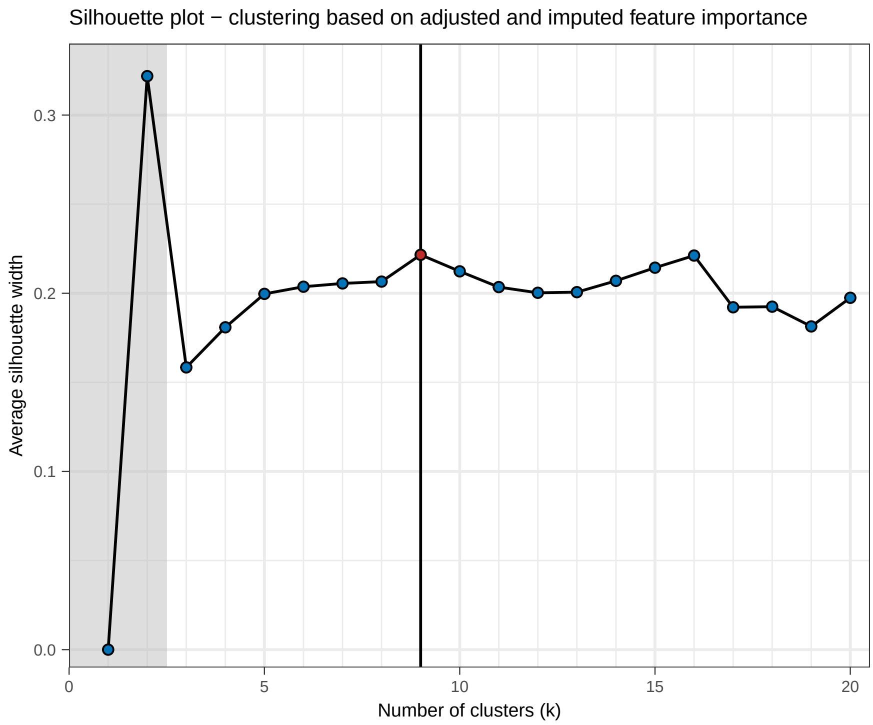
(B.5.3) Average silhouette width for different numbers of clusters k

This figure shows the average silhouette width across all clusters for different numbers of clusters k. We perform k-means clustering on a dataset with 88 observations at the country level. Observations include information on feature importance and the vertical distribution. In contrast to Figure B.5.1, we do not adjust feature importance for country-level model performance. Vertical line and red point indicate the number of clusters that maximizes average silhouette width across all clusters with $k \geq 3$.



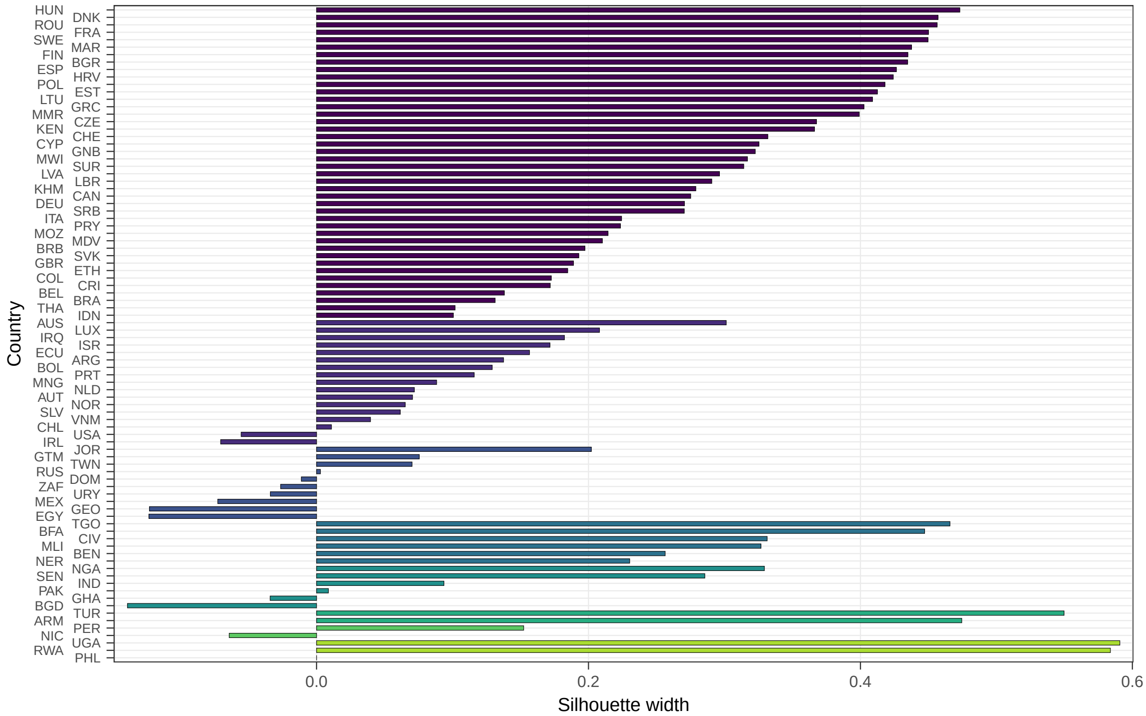
(B.5.4) Average silhouette width for each country per cluster k

This figure shows the silhouette for each country for 11 clusters. We perform k-means clustering on a dataset with 88 observations at the country level. Observations include information on feature importance and the vertical distribution. In contrast to Figure B.5.4, we do not adjust feature importance for country-level model performance. We order observations (y-axis) by clusters with most observations and by silhouette width. Silhouette width expresses how well each observation fits in its cluster, also in comparison to the observations from the least distant, but different cluster.



(B.5.5) Average silhouette width for different numbers of clusters k

This figure shows the average silhouette width across all clusters for different numbers of clusters k. We perform k-means clustering on a dataset with 88 observations at the country level. Observations include information on feature importance and the vertical distribution. In contrast to Figure B.5.1, we impute missing values for unobserved features with the average feature importance for each feature. We adjust feature importance for country-level model performance. Vertical line and red point indicate the number of clusters that maximizes average silhouette width across all clusters with $k \geq 3$.



(B.5.6) Average silhouette width for each country per cluster k

This figure shows the silhouette for each country for 9 clusters. We perform k-means clustering on a dataset with 88 observations at the country level. Observations include information feature importance and the vertical distribution. In contrast to Figure B.5.4, we impute missing values for unobserved features with the average feature importance for each feature. We adjust feature importance for country-level model performance. We order observations (y-axis) by clusters with most observations and by silhouette width. Silhouette width expresses how well each observation fits in its cluster, also in comparison to the observations from the least distant, but different cluster.

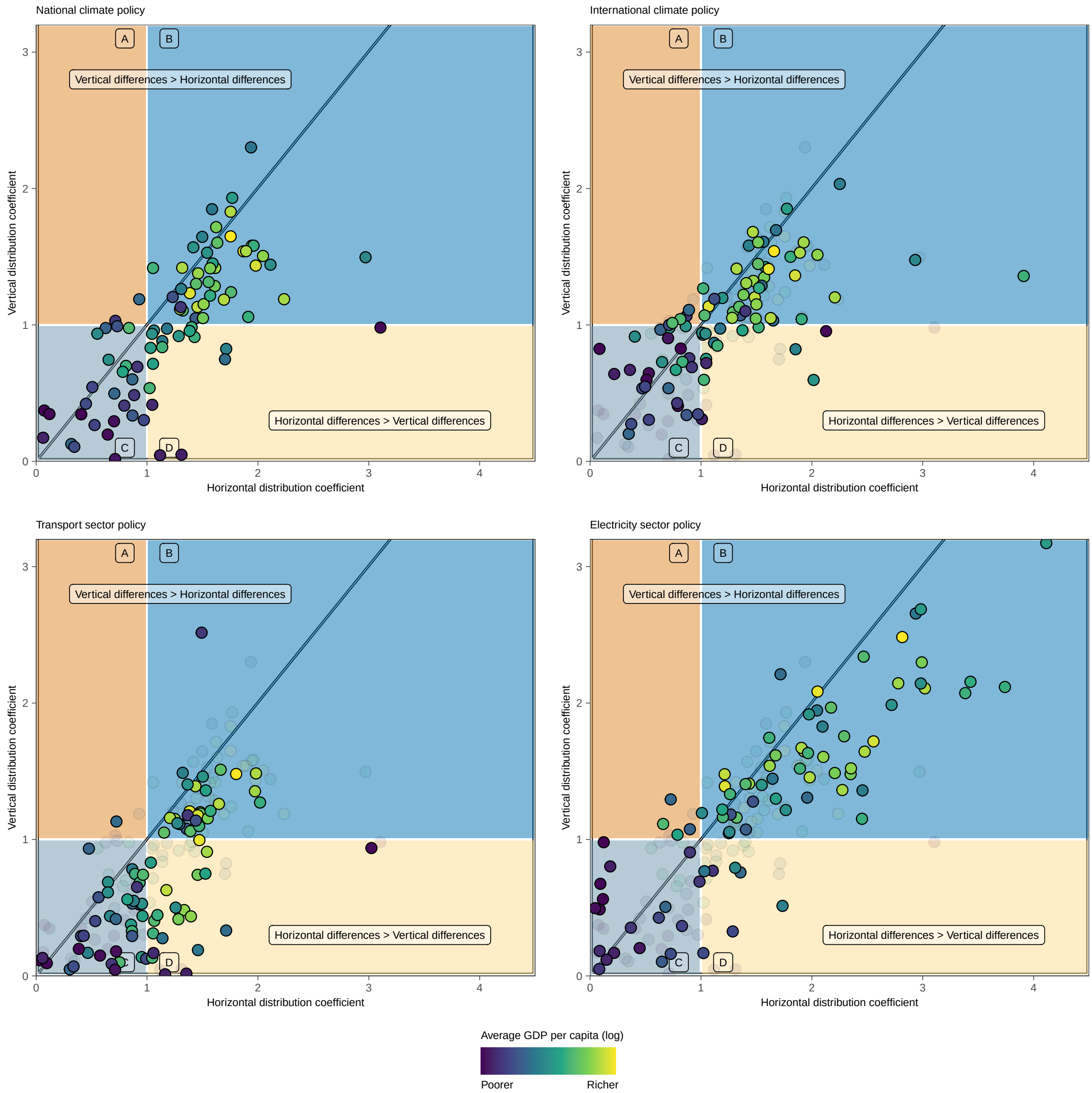


Figure B.6: Vertical and horizontal distribution coefficients for different policies

This figure displays the vertical distribution coefficient comparing the median carbon intensity of the richest and the poorest quintile. The horizontal distribution coefficient compares the within-quintile differences (5^{th} to 95^{th} percentile within quintiles) of the richest and the poorest quintile. Rectangles (A) and (B) indicate higher carbon intensity (at the median) among the poorest quintile compared to the richest quintile; rectangles (C) and (D) indicate lower carbon intensity (at the median) among the poorest quintile compared to the richest quintile. Rectangles (A) and (C) indicate smaller within-quintile differences of carbon intensity among the poorest quintile compared to the richest quintile; rectangles (B) and (D) indicate larger within-quintile differences of carbon intensity among the poorest quintile compared to the richest quintile. Colors of points indicate GDP per capita for 2018 (in log-transformed constant 2010 USD).

Panel 'National climate policy' shows the same values as Figure 2, i.e., distribution coefficients for carbon intensities accounting for all nationally released CO_2 emissions across all sectors. Panel 'International climate policy' shows distribution coefficients for carbon intensities accounting for global O_2 emissions embedded in national consumption. Panels 'Transport sector policy' and 'Electricity sector policy' display distribution coefficients for carbon intensities accounting for nationally released CO_2 emissions in the transport sector and electricity sector, respectively.

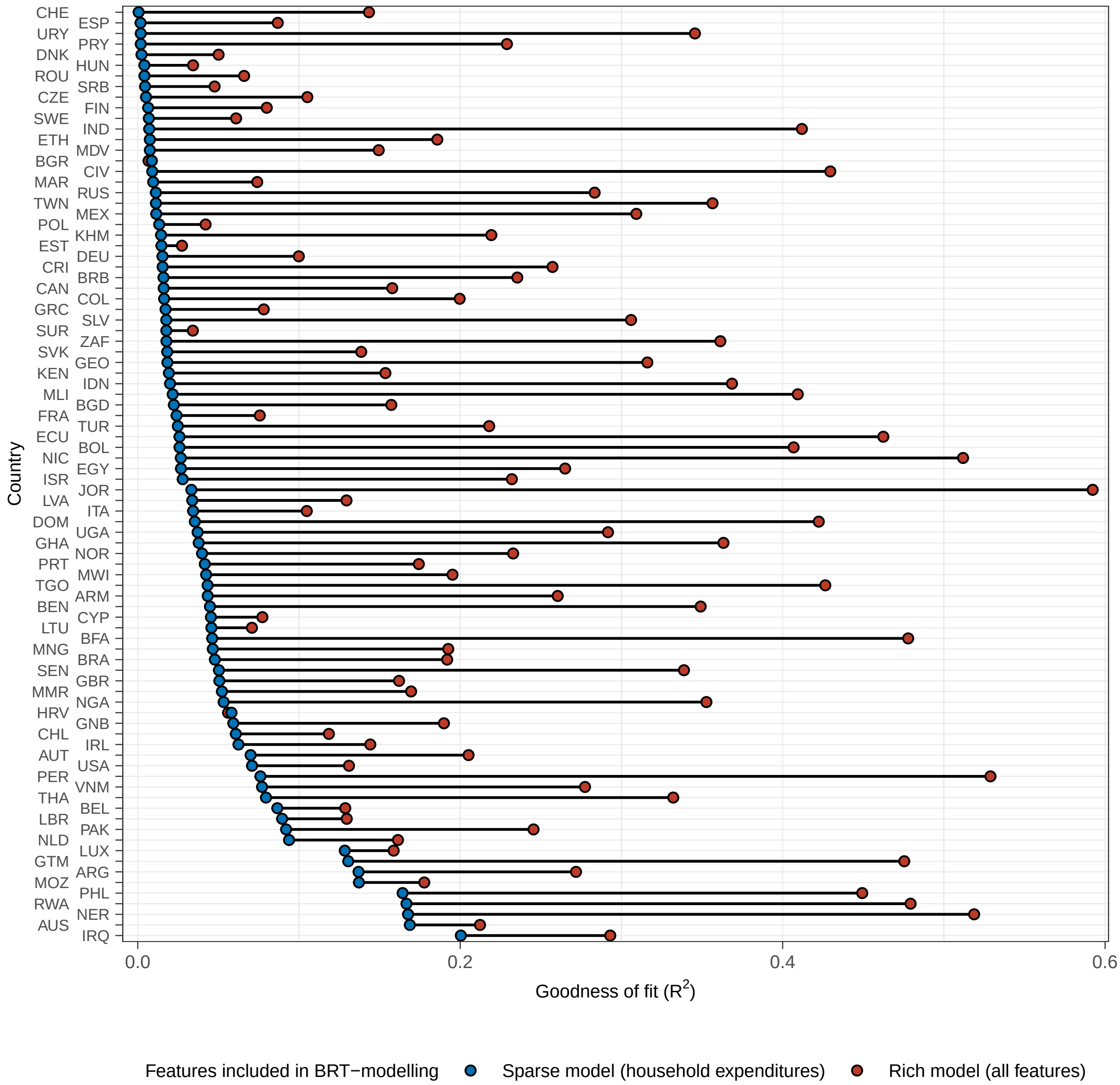
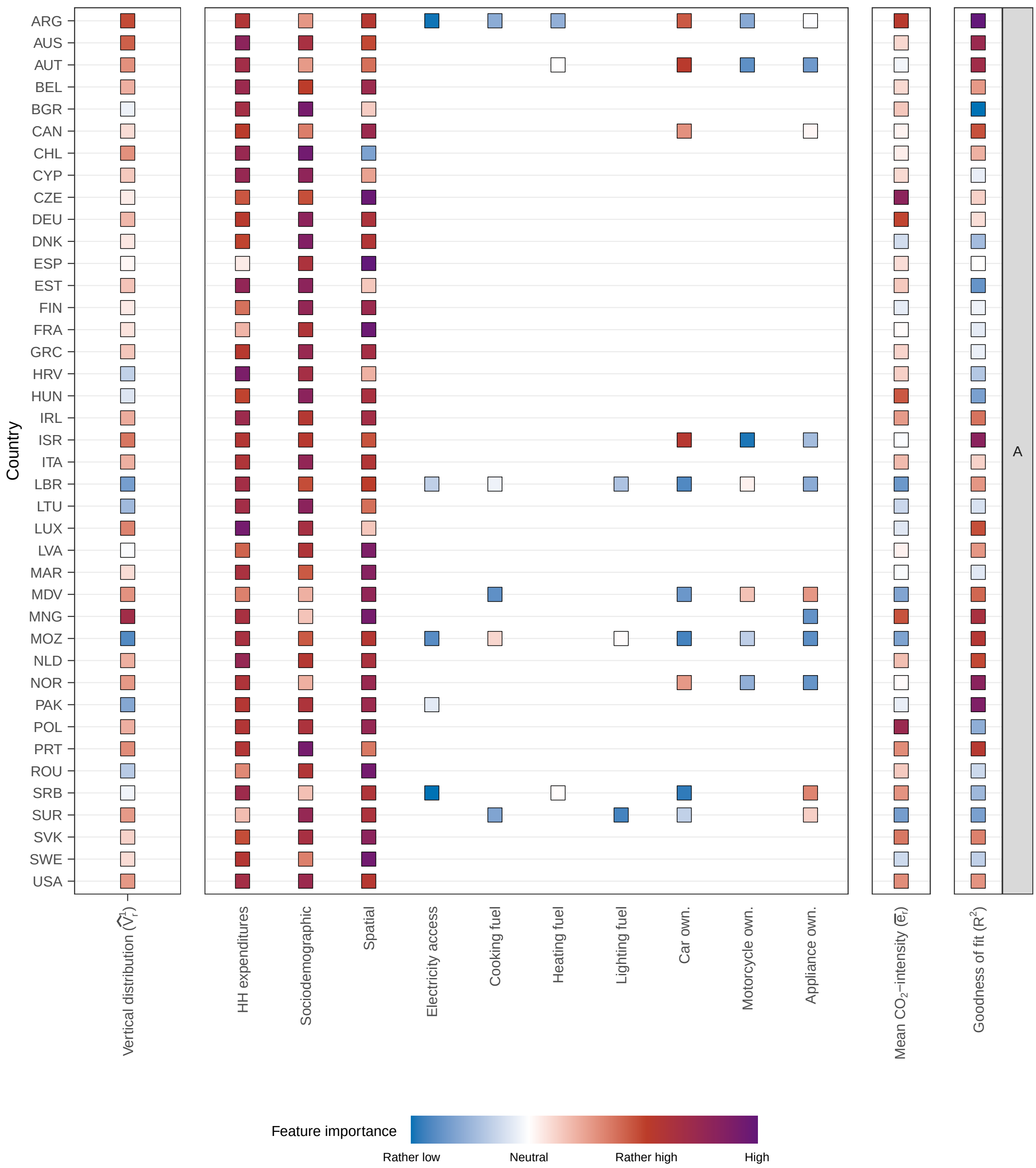


Figure B.7: Goodness of fit (R^2) for rich and sparse BRT models

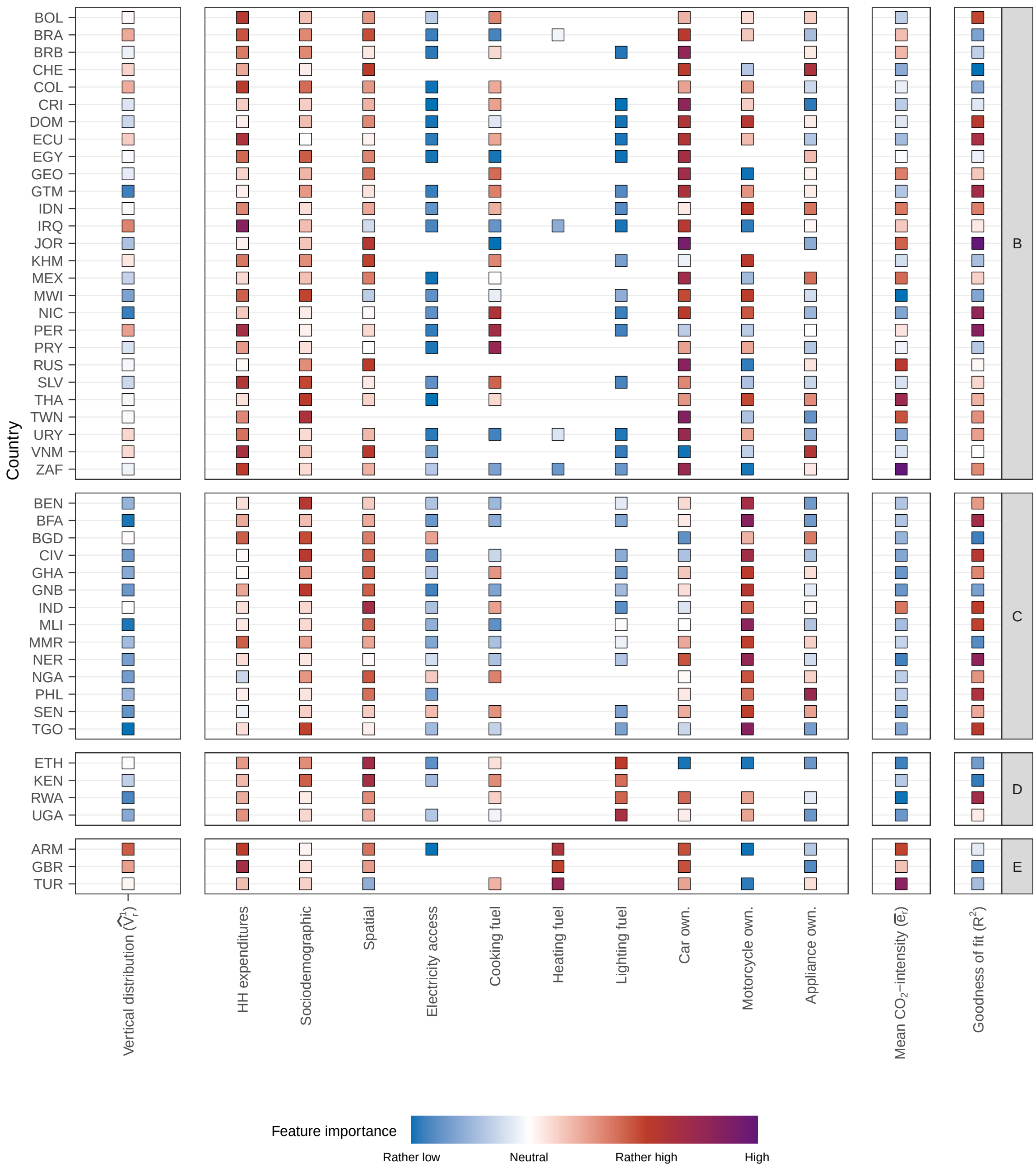
This figure shows goodness of fit (R^2) for sparse and rich boosted regression tree models. The sparse models include household expenditures as feature (blue point) and the rich models include all available features (red point), including household expenditures. We tune hyperparameters for each country and set of features and use fivefold cross-validation for evaluating model performance. See also table C.10 for country-level MAE and RMSE.

Figure B.8: Feature importance across countries by cluster - Alternative clustering



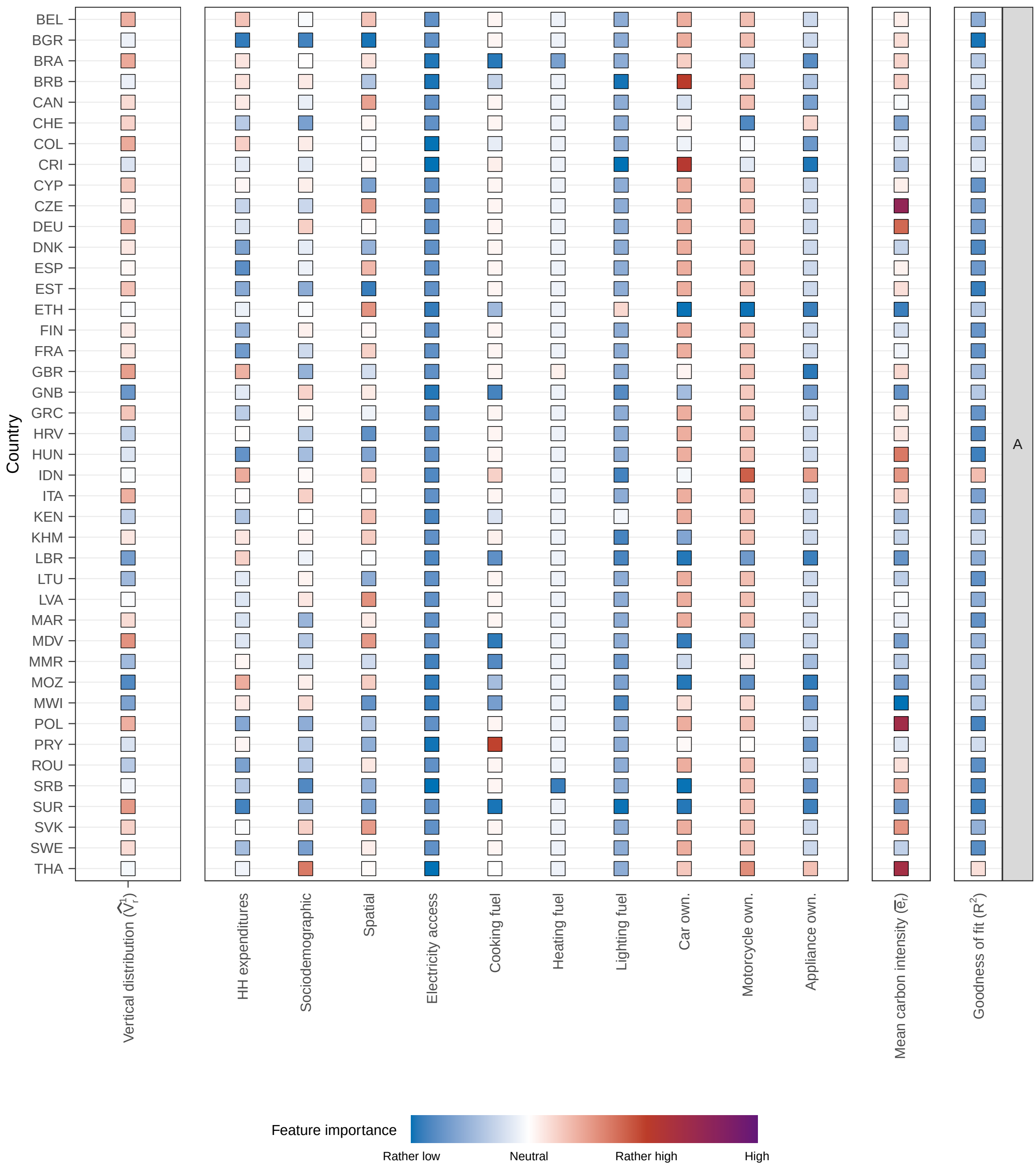
(B.8.1) Feature importance across countries of cluster A to C - non-adjusted

This figure shows the importance of features (in normalized average absolute SHAP-values) for each country, grouped by 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' comprises features such as household size, gender, self-identified ethnicity, nationality, religion, or language. 'Spatial' comprises features such as state, province, district, and urban/rural identifiers. For vertical distribution, blue (red) colors indicate lower (higher) median carbon intensity among 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 goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity and R^2 are not explicitly included for clustering. We assign countries to five clusters performing k-means clustering based on *non-adjusted* feature importance values across all features. We also show all values in Table C.12.



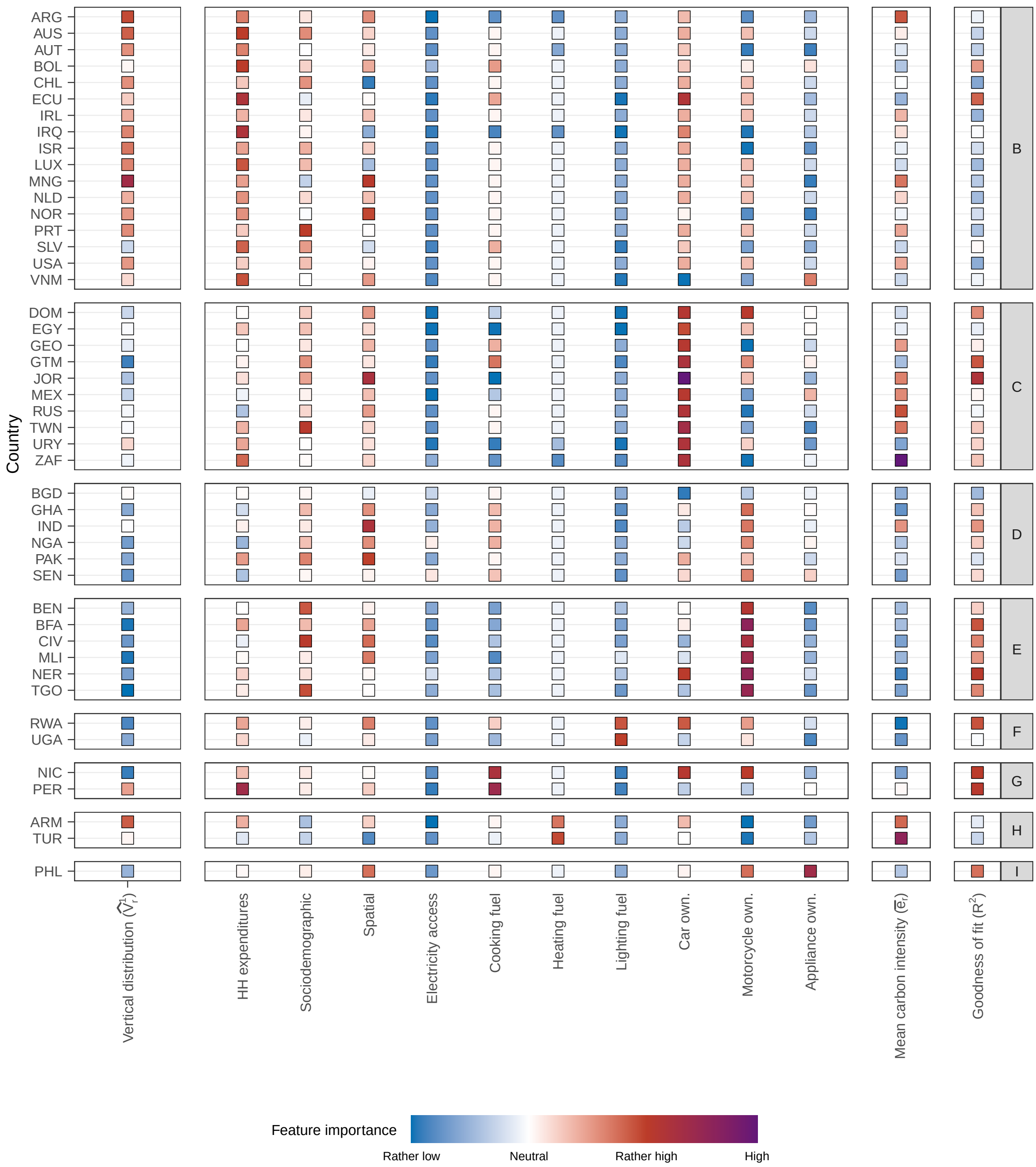
(B.8.2) Feature importance across countries of clusters D to L - non-adjusted

This figure shows the importance of features (in normalized average absolute SHAP-values) for each country, grouped by 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' comprises features such as household size, gender, self-identified ethnicity, nationality, religion, or language. 'Spatial' comprises features such as state, province, district, and urban/rural identifiers. For vertical distribution, blue (red) colors indicate lower (higher) median carbon intensity among 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 goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity and R^2 are not explicitly included for clustering. We assign countries to five clusters performing k-means clustering based on *non-adjusted* feature importance values across all features. We also show all values in Table C.12.



(B.8.3) Feature importance across countries of clusters A to B - imputed

This figure shows the importance of features (in normalized average absolute SHAP-values) for each country, grouped by country clusters. In contrast to figure 3, we impute missing values for unobserved features with the average feature importance for each feature. We adjust feature importance for country-level model performance. Blue (red) colors indicate that a feature is relatively less (more) important in a country compared to all other countries and features. 'Sociodemographic' comprises features such as household size, gender, self-identified ethnicity, nationality, religion, or language. 'Spatial' comprises features such as state, province, district, and urban/rural identifiers. For vertical distribution, blue (red) colors indicate lower (higher) median carbon intensity among 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 goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity and R^2 are not explicitly included for clustering. We assign countries to nine clusters performing k-means clustering based on *adjusted* and *imputed* feature importance values across all features. We also show all values in Table C.13.



(B.8.4) Feature importance across countries of clusters C to K - imputed

This figure shows the importance of features (in normalized average absolute SHAP-values) for each country, grouped by country clusters. In contrast to figure 3, we impute missing values for unobserved features with the average feature importance for each feature. We adjust feature importance for country-level model performance. Blue (red) colors indicate that a feature is relatively less (more) important in a country compared to all other countries and features. 'Sociodemographic' comprises features such as household size, gender, self-identified ethnicity, nationality, religion, or language. 'Spatial' comprises features such as state, province, district, and urban/rural identifiers. For vertical distribution, blue (red) colors indicate lower (higher) median carbon intensity among 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 goodness of fit (R^2), blue (red) colors indicate a lower (higher) predictive performance compared to other countries. Average carbon intensity and R^2 are not explicitly included for clustering. We assign countries to nine clusters performing k-means clustering based on *adjusted* and *imputed* feature importance values across all features. We also show all values in Table C.13.

Figure B.9: Partial dependence plot (SHAP) for 88 countries and nine clusters

(B.9.1) Partial dependence plot (SHAP) for Argentina (cluster A)

../1_Figures//Figure 5b/Figure_5b_ARG.jpg

(B.9.2) Partial dependence plot (SHAP) for Australia (cluster A)

../1_Figures//Figure 5b/Figure_5b_AUS.jpg

(B.9.3) Partial dependence plot (SHAP) for Austria (cluster A)

../1_Figures//Figure 5b/Figure_5b_AUT.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.4) Partial dependence plot (SHAP) for Belgium (cluster A)

../1_Figures//Figure 5b/Figure_5b_BEL.jpg

(B.9.5) Partial dependence plot (SHAP) for Bangladesh (cluster A)

../1_Figures//Figure 5b/Figure_5b_BGD.jpg

(B.9.6) Partial dependence plot (SHAP) for Bulgaria (cluster A)

../1_Figures//Figure 5b/Figure_5b_BGR.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.7) Partial dependence plot (SHAP) for Brazil (cluster A)

../1_Figures//Figure 5b/Figure_5b_BRA.jpg

(B.9.8) Partial dependence plot (SHAP) for Canada (cluster A)

../1_Figures//Figure 5b/Figure_5b_CAN.jpg

(B.9.9) Partial dependence plot (SHAP) for Switzerland (cluster A)

../1_Figures//Figure 5b/Figure_5b_CHE.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.10) Partial dependence plot (SHAP) for Chile (cluster A)

../1_Figures//Figure 5b/Figure_5b_CHL.jpg

(B.9.11) Partial dependence plot (SHAP) for Colombia (cluster A)

../1_Figures//Figure 5b/Figure_5b_COL.jpg

(B.9.12) Partial dependence plot (SHAP) for Cyprus (cluster A)

../1_Figures//Figure 5b/Figure_5b_CYP.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.13) Partial dependence plot (SHAP) for Czech Republic (cluster A)

../1_Figures//Figure 5b/Figure_5b_CZE.jpg

(B.9.14) Partial dependence plot (SHAP) for Germany (cluster A)

../1_Figures//Figure 5b/Figure_5b_DEU.jpg

(B.9.15) Partial dependence plot (SHAP) for Denmark (cluster A)

../1_Figures//Figure 5b/Figure_5b_DNK.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.16) Partial dependence plot (SHAP) for Spain (cluster A)

../1_Figures//Figure 5b/Figure_5b_ESP.jpg

(B.9.17) Partial dependence plot (SHAP) for Estonia (cluster A)

../1_Figures//Figure 5b/Figure_5b_EST.jpg

(B.9.18) Partial dependence plot (SHAP) for Ethiopia (cluster A)

../1_Figures//Figure 5b/Figure_5b_ETH.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.19) Partial dependence plot (SHAP) for Finland (cluster A)

../1_Figures//Figure 5b/Figure_5b_FIN.jpg

(B.9.20) Partial dependence plot (SHAP) for France (cluster A)

../1_Figures//Figure 5b/Figure_5b_FRA.jpg

(B.9.21) Partial dependence plot (SHAP) for United Kingdom (cluster A)

../1_Figures//Figure 5b/Figure_5b_GBR.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.22) Partial dependence plot (SHAP) for Guinea-Bissau (cluster A)

../1_Figures//Figure 5b/Figure_5b_GNB.jpg

(B.9.23) Partial dependence plot (SHAP) for Greece (cluster A)

../1_Figures//Figure 5b/Figure_5b_GRC.jpg

(B.9.24) Partial dependence plot (SHAP) for Croatia (cluster A)

../1_Figures//Figure 5b/Figure_5b_HRV.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.25) Partial dependence plot (SHAP) for Hungary (cluster A)

../1_Figures//Figure 5b/Figure_5b_HUN.jpg

(B.9.26) Partial dependence plot (SHAP) for Ireland (cluster A)

../1_Figures//Figure 5b/Figure_5b_IRL.jpg

(B.9.27) Partial dependence plot (SHAP) for Israel (cluster A)

../1_Figures//Figure 5b/Figure_5b_ISR.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.28) Partial dependence plot (SHAP) for Italy (cluster A)

../1_Figures//Figure 5b/Figure_5b_ITA.jpg

(B.9.29) Partial dependence plot (SHAP) for Kenya (cluster A)

../1_Figures//Figure 5b/Figure_5b_KEN.jpg

(B.9.30) Partial dependence plot (SHAP) for Cambodia (cluster A)

../1_Figures//Figure 5b/Figure_5b_KHM.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.31) Partial dependence plot (SHAP) for Liberia (cluster A)

../1_Figures//Figure 5b/Figure_5b_LBR.jpg

(B.9.32) Partial dependence plot (SHAP) for Lithuania (cluster A)

../1_Figures//Figure 5b/Figure_5b_LTU.jpg

(B.9.33) Partial dependence plot (SHAP) for Luxemburg (cluster A)

../1_Figures//Figure 5b/Figure_5b_LUX.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.34) Partial dependence plot (SHAP) for Latvia (cluster A)

../1_Figures//Figure 5b/Figure_5b_LVA.jpg

(B.9.35) Partial dependence plot (SHAP) for Morocco (cluster A)

../1_Figures//Figure 5b/Figure_5b_MAR.jpg

(B.9.36) Partial dependence plot (SHAP) for Maldives (cluster A)

../1_Figures//Figure 5b/Figure_5b_MDV.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.37) Partial dependence plot (SHAP) for Myanmar (cluster A)

../1_Figures//Figure 5b/Figure_5b_MMR.jpg

(B.9.38) Partial dependence plot (SHAP) for Mongolia (cluster A)

../1_Figures//Figure 5b/Figure_5b_MNG.jpg

(B.9.39) Partial dependence plot (SHAP) for Mozambique (cluster A)

../1_Figures//Figure 5b/Figure_5b_MOZ.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.40) Partial dependence plot (SHAP) for Malawi (cluster A)

../1_Figures//Figure 5b/Figure_5b_MWI.jpg

(B.9.41) Partial dependence plot (SHAP) for the Netherlands (cluster A)

../1_Figures//Figure 5b/Figure_5b_NLD.jpg

(B.9.42) Partial dependence plot (SHAP) for Norway (cluster A)

../1_Figures//Figure 5b/Figure_5b_NOR.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.43) Partial dependence plot (SHAP) for Poland (cluster A)

../1_Figures//Figure 5b/Figure_5b_POL.jpg

(B.9.44) Partial dependence plot (SHAP) for Portugal (cluster A)

../1_Figures//Figure 5b/Figure_5b_PRT.jpg

(B.9.45) Partial dependence plot (SHAP) for Romania (cluster A)

../1_Figures//Figure 5b/Figure_5b_ROU.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.46) Partial dependence plot (SHAP) for Serbia (cluster A)

../1_Figures//Figure 5b/Figure_5b_SRB.jpg

(B.9.47) Partial dependence plot (SHAP) for Suriname (cluster A)

../1_Figures//Figure 5b/Figure_5b_SUR.jpg

(B.9.48) Partial dependence plot (SHAP) for Slovakia (cluster A)

../1_Figures//Figure 5b/Figure_5b_SVK.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.49) Partial dependence plot (SHAP) for Sweden (cluster A)

../1_Figures//Figure 5b/Figure_5b_SWE.jpg

(B.9.50) Partial dependence plot (SHAP) for USA (cluster A)

../1_Figures//Figure 5b/Figure_5b_USA.jpg

(B.9.51) Partial dependence plot (SHAP) for Barbados (cluster B)

../1_Figures//Figure 5b/Figure_5b_BRB.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.52) Partial dependence plot (SHAP) for Costa Rica (cluster B)

../1_Figures//Figure 5b/Figure_5b_CRI.jpg

(B.9.53) Partial dependence plot (SHAP) for Dominican Republic (cluster B)

../1_Figures//Figure 5b/Figure_5b_DOM.jpg

(B.9.54) Partial dependence plot (SHAP) for Egypt (cluster B)

../1_Figures//Figure 5b/Figure_5b_EGY.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.55) Partial dependence plot (SHAP) for Georgia (cluster B)

../1_Figures//Figure 5b/Figure_5b_GEO.jpg

(B.9.56) Partial dependence plot (SHAP) for Guatemala (cluster B)

../1_Figures//Figure 5b/Figure_5b_GTM.jpg

(B.9.57) Partial dependence plot (SHAP) for Indonesia (cluster B)

../1_Figures//Figure 5b/Figure_5b_IDN.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.58) Partial dependence plot (SHAP) for Jordan (cluster B)

../1_Figures//Figure 5b/Figure_5b_JOR.jpg

(B.9.59) Partial dependence plot (SHAP) for Mexico (cluster B)

../1_Figures//Figure 5b/Figure_5b_MEX.jpg

(B.9.60) Partial dependence plot (SHAP) for the Philippines (cluster B)

../1_Figures//Figure 5b/Figure_5b_PHL.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.61) Partial dependence plot (SHAP) for Russian Federation (cluster B)

../1_Figures//Figure 5b/Figure_5b_RUS.jpg

(B.9.62) Partial dependence plot (SHAP) for Thailand (cluster B)

../1_Figures//Figure 5b/Figure_5b_THA.jpg

(B.9.63) Partial dependence plot (SHAP) for Taiwan (cluster B)

../1_Figures//Figure 5b/Figure_5b_TWN.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.64) Partial dependence plot (SHAP) for Uruguay (cluster B)

../1_Figures//Figure 5b/Figure_5b_URY.jpg

(B.9.65) Partial dependence plot (SHAP) for Vietnam (cluster B)

../1_Figures//Figure 5b/Figure_5b_VNM.jpg

(B.9.66) Partial dependence plot (SHAP) for South Africa (cluster B)

../1_Figures//Figure 5b/Figure_5b_ZAF.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.67) Partial dependence plot (SHAP) for Benin (cluster C)

../1_Figures//Figure 5b/Figure_5b_BEN.jpg

(B.9.68) Partial dependence plot (SHAP) for Burkina Faso (cluster C)

../1_Figures//Figure 5b/Figure_5b_BFA.jpg

(B.9.69) Partial dependence plot (SHAP) for Côte d'Ivoire (cluster C)

../1_Figures//Figure 5b/Figure_5b_CIV.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.70) Partial dependence plot (SHAP) for Ghana (cluster C)

../1_Figures//Figure 5b/Figure_5b_GHA.jpg

(B.9.71) Partial dependence plot (SHAP) for India (cluster C)

../1_Figures//Figure 5b/Figure_5b_IND.jpg

(B.9.72) Partial dependence plot (SHAP) for Mali (cluster C)

../1_Figures//Figure 5b/Figure_5b_MLI.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.73) Partial dependence plot (SHAP) for Niger (cluster C)

../1_Figures//Figure 5b/Figure_5b_NER.jpg

(B.9.74) Partial dependence plot (SHAP) for Nigeria (cluster C)

../1_Figures//Figure 5b/Figure_5b_NGA.jpg

(B.9.75) Partial dependence plot (SHAP) for Pakistan (cluster C)

../1_Figures//Figure 5b/Figure_5b_PAK.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.76) Partial dependence plot (SHAP) for Senegal (cluster C)

../1_Figures//Figure 5b/Figure_5b_SEN.jpg

(B.9.77) Partial dependence plot (SHAP) for Togo (cluster C)

../1_Figures//Figure 5b/Figure_5b_TGO.jpg

(B.9.78) Partial dependence plot (SHAP) for Bolivia (cluster D)

../1_Figures//Figure 5b/Figure_5b_BOL.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.79) Partial dependence plot (SHAP) for Ecuador (cluster D)

../1_Figures//Figure 5b/Figure_5b_ECU.jpg

(B.9.80) Partial dependence plot (SHAP) for Iraq (cluster D)

../1_Figures//Figure 5b/Figure_5b_IRQ.jpg

(B.9.81) Partial dependence plot (SHAP) for Nicaragua (cluster D)

../1_Figures//Figure 5b/Figure_5b_NIC.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.82) Partial dependence plot (SHAP) for Peru (cluster D)

../1_Figures//Figure 5b/Figure_5b_PER.jpg

(B.9.83) Partial dependence plot (SHAP) for Paraguay (cluster D)

../1_Figures//Figure 5b/Figure_5b_PRY.jpg

(B.9.84) Partial dependence plot (SHAP) for El Salvador (cluster D)

../1_Figures//Figure 5b/Figure_5b_SLV.jpg

This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.85) Partial dependence plot (SHAP) for Rwanda (cluster E)

../1_Figures//Figure 5b/Figure_5b_RWA.jpg

(B.9.86) Partial dependence plot (SHAP) for Uganda (cluster E)

../1_Figures//Figure 5b/Figure_5b_UGA.jpg

(B.9.87) Partial dependence plot (SHAP) for Armenia (cluster F)

../1_Figures//Figure 5b/Figure_5b_ARM.jpg

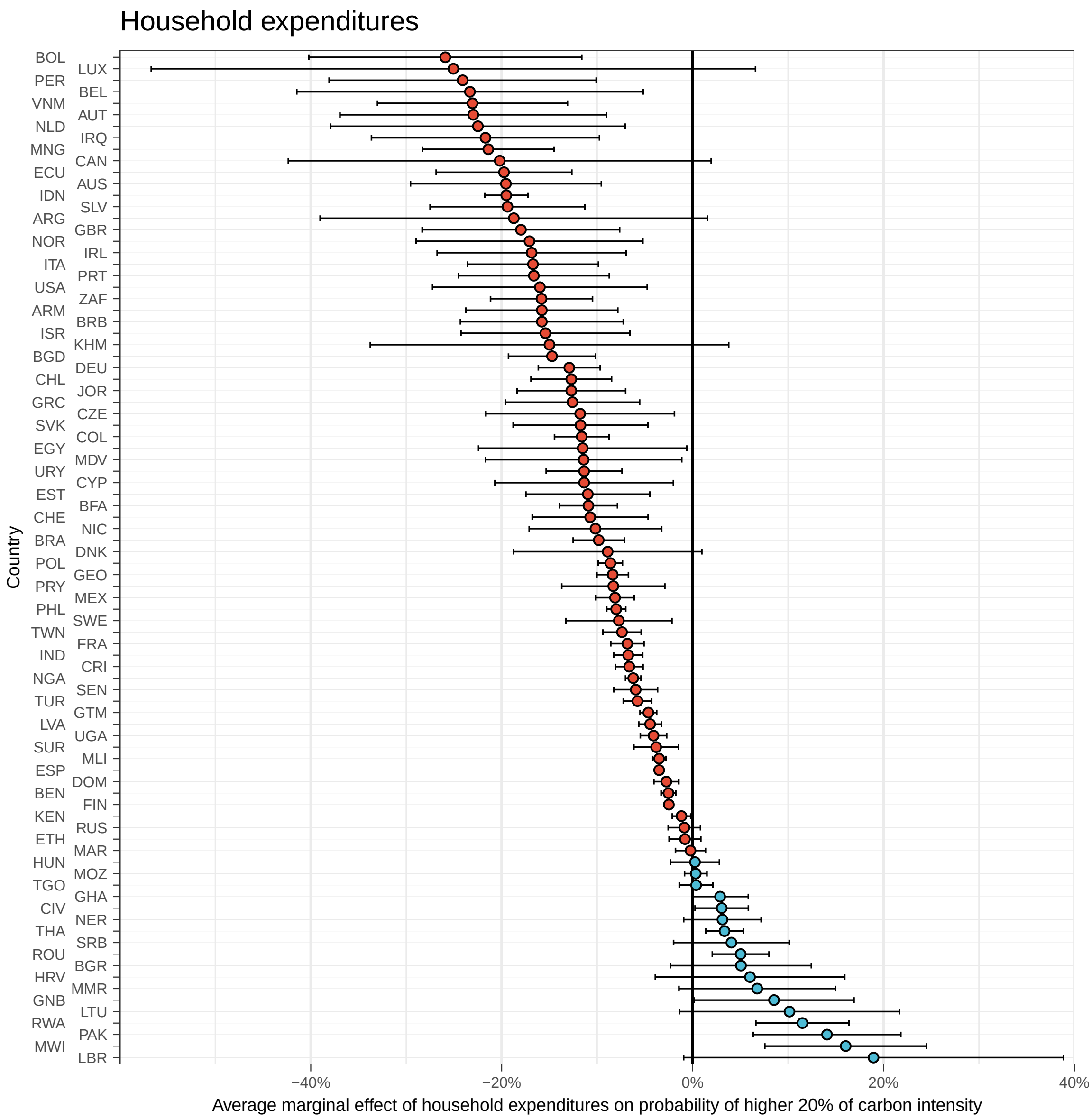
This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

(B.9.88) Partial dependence plot (SHAP) for Turkey (cluster F)

../1_Figures//Figure 5b/Figure_5b_TUR.jpg

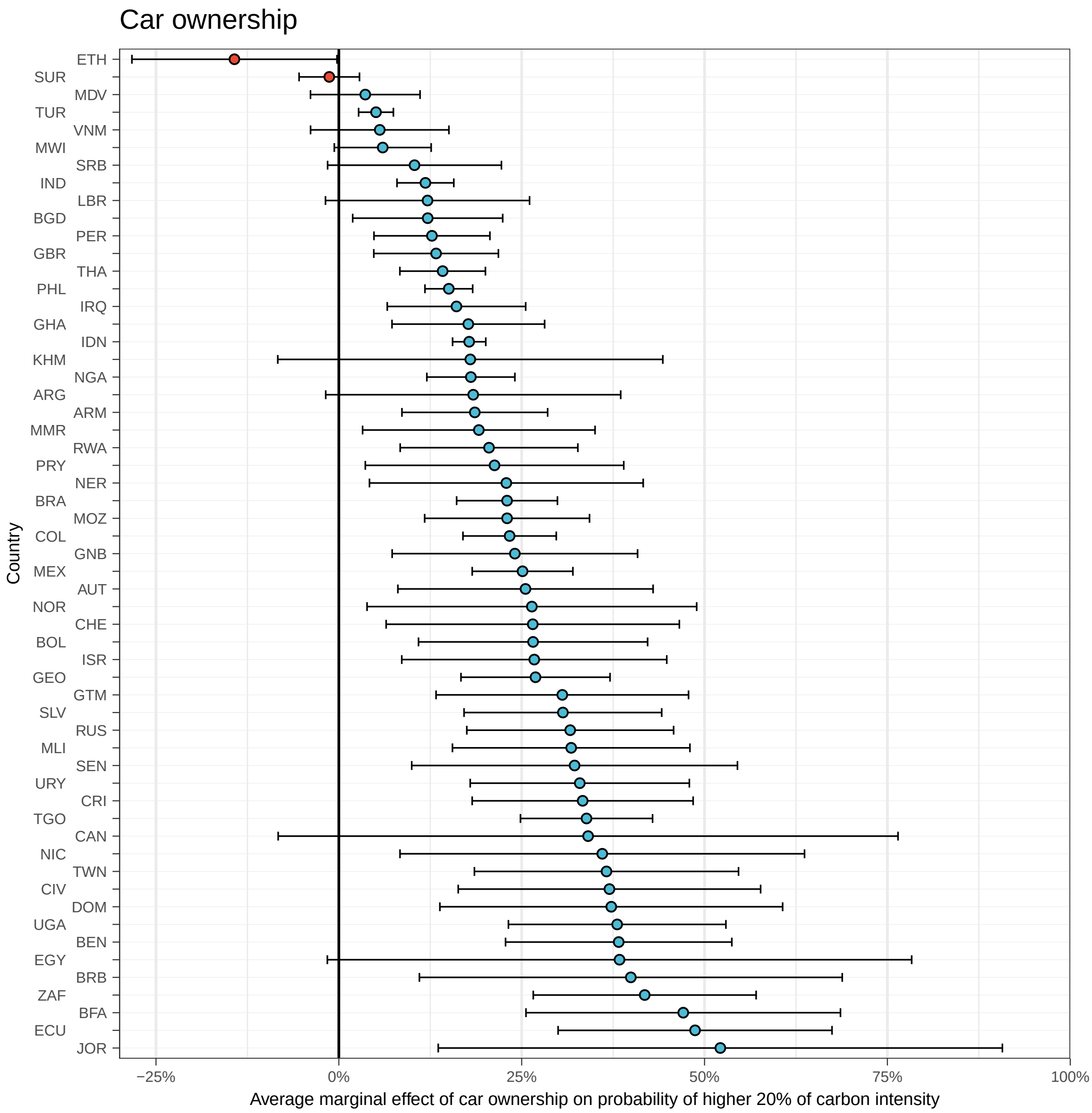
This figure shows SHAP-values for predicting carbon intensity over feature values for 88 countries in alphabetical order for six country-clusters. The bar chart displays normalized average absolute SHAP-values for all features. Features with less than 3% of normalized SHAP-values are subsumed as "Other features (Sum)". Panels show SHAP-values over total household expenditures for all countries and for the three most important features in each country besides total household expenditures. Colors represent household expenditures with blue (red) colors indicating lower (higher) household expenditures.

Figure B.10: Average marginal effects (logit models)



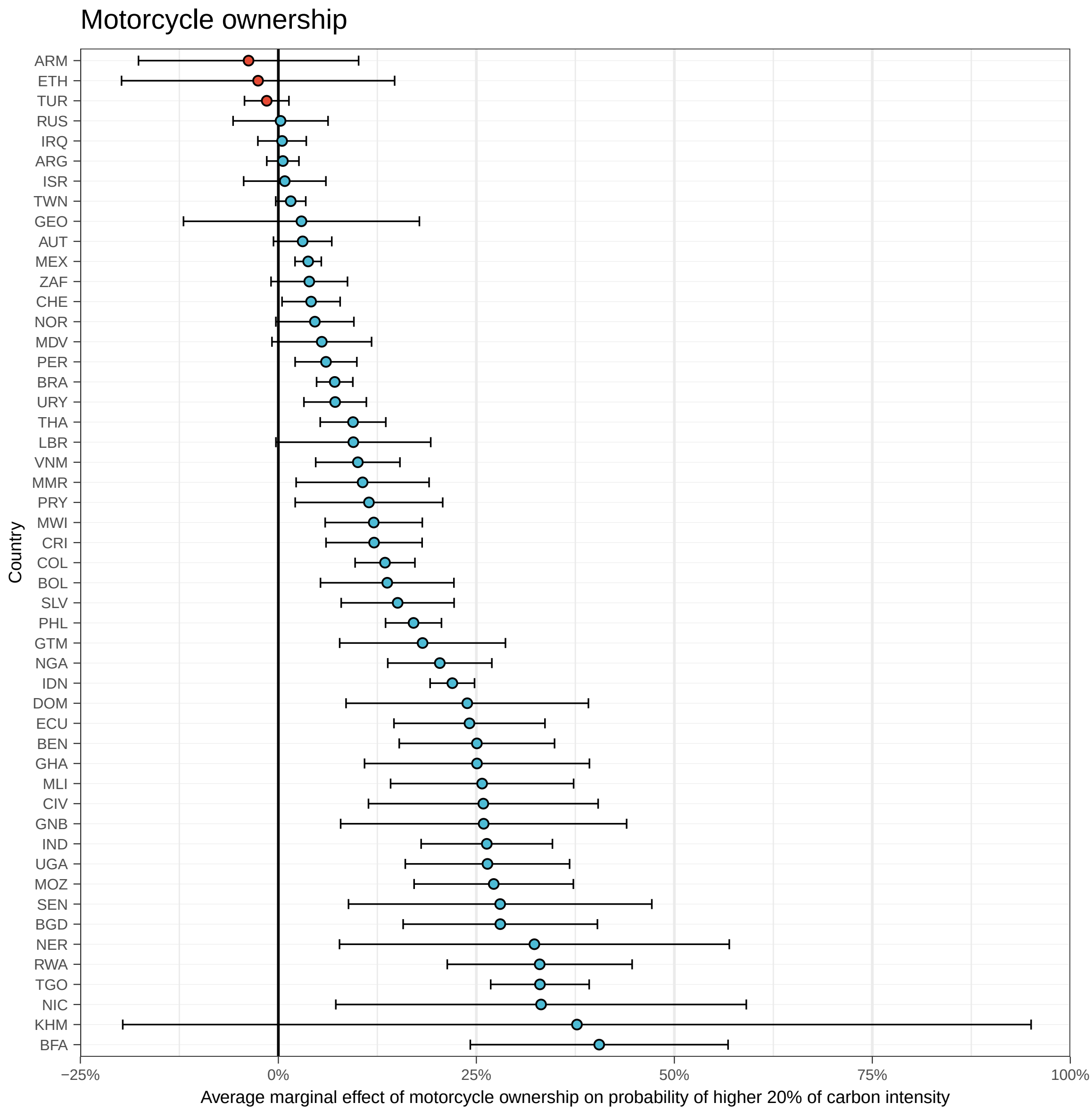
(B.10.1) Average marginal effects of total household expenditures (log)

This figure shows average marginal effects of 1% increase in total household expenditures on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



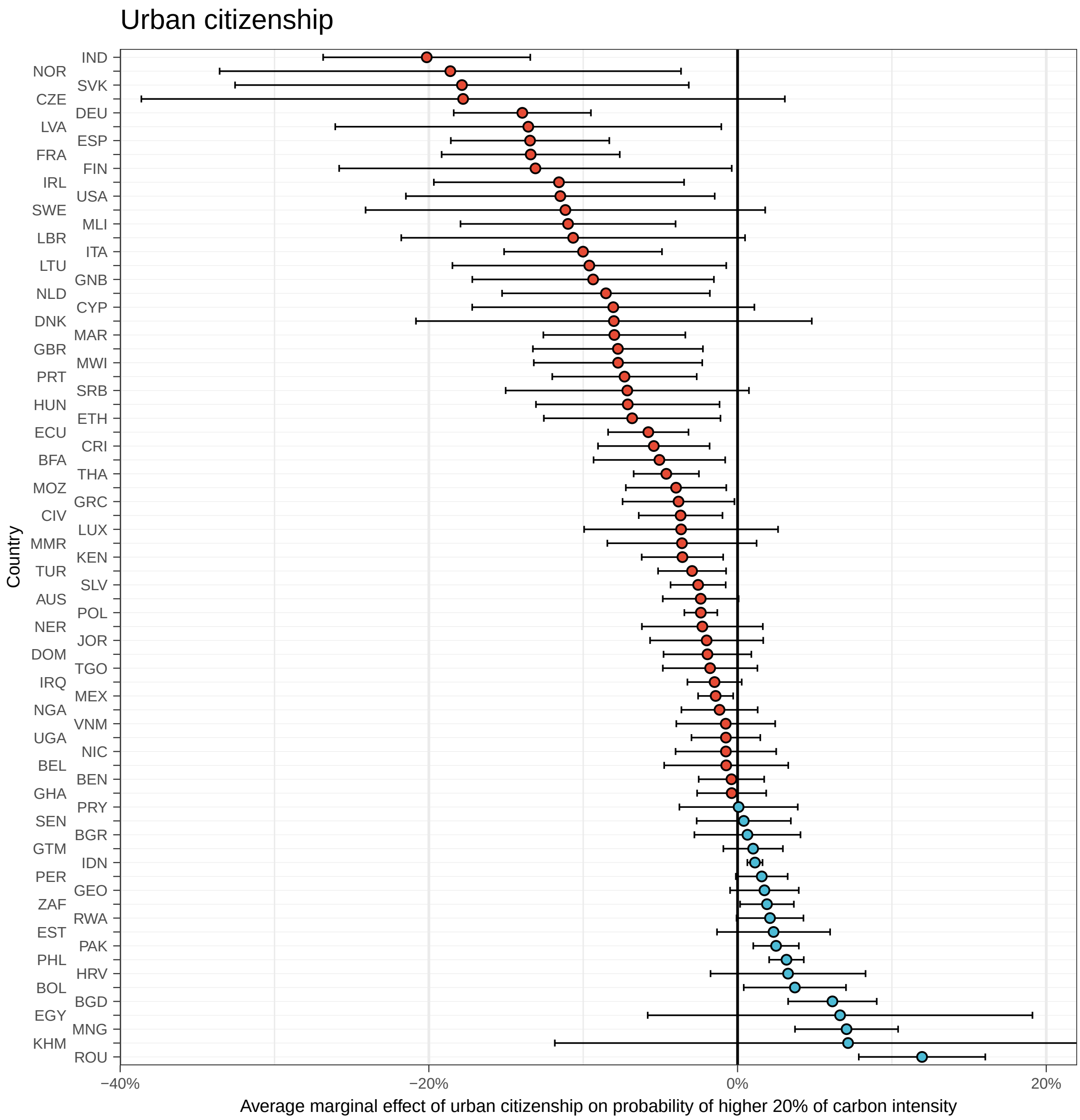
(B.10.2) Average marginal effects of car ownership

This figure shows average marginal effects of car ownership on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



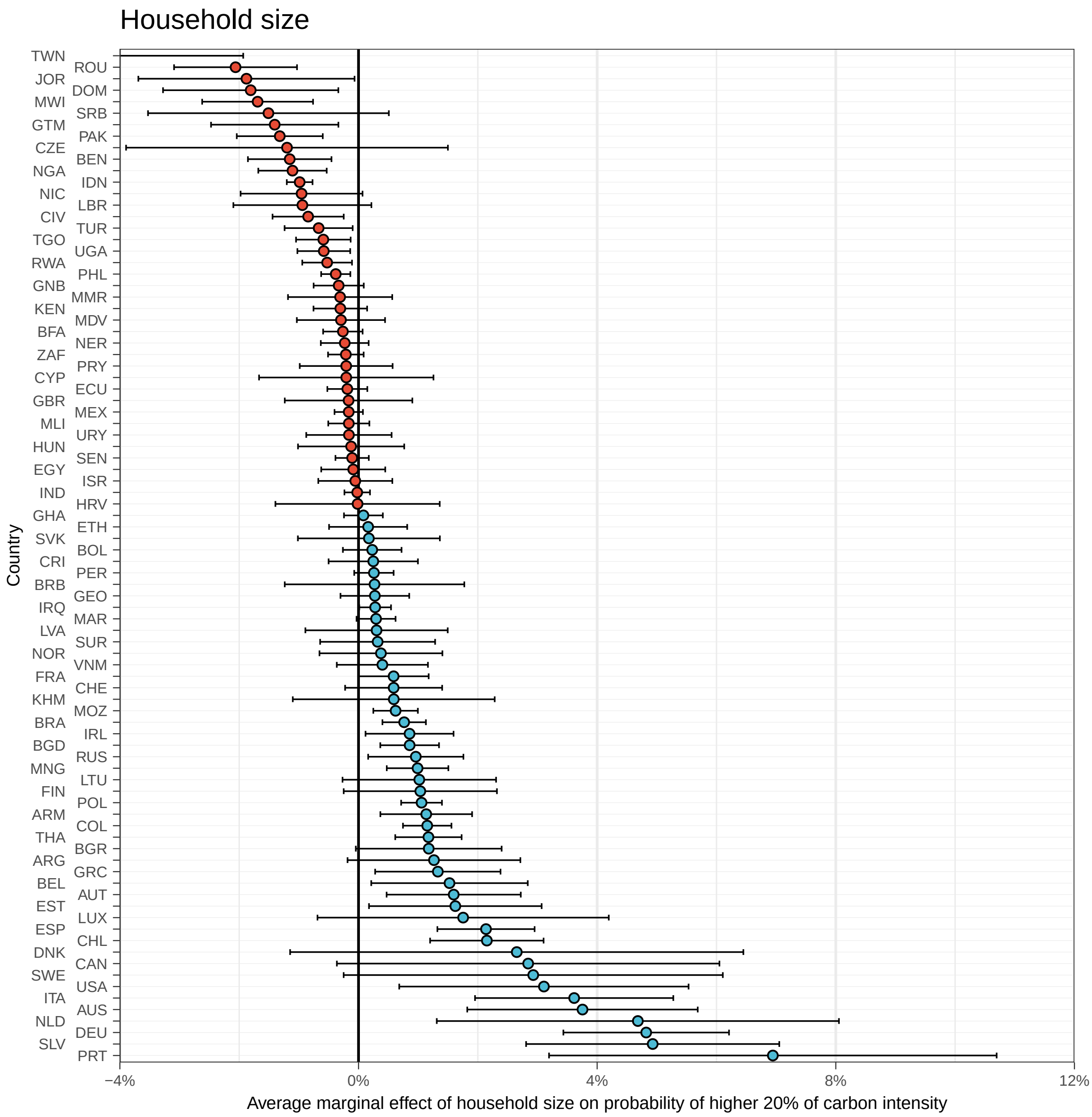
(B.10.3) Average marginal effects of motorcycle ownership

This figure shows average marginal effects of motorcycle ownership on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



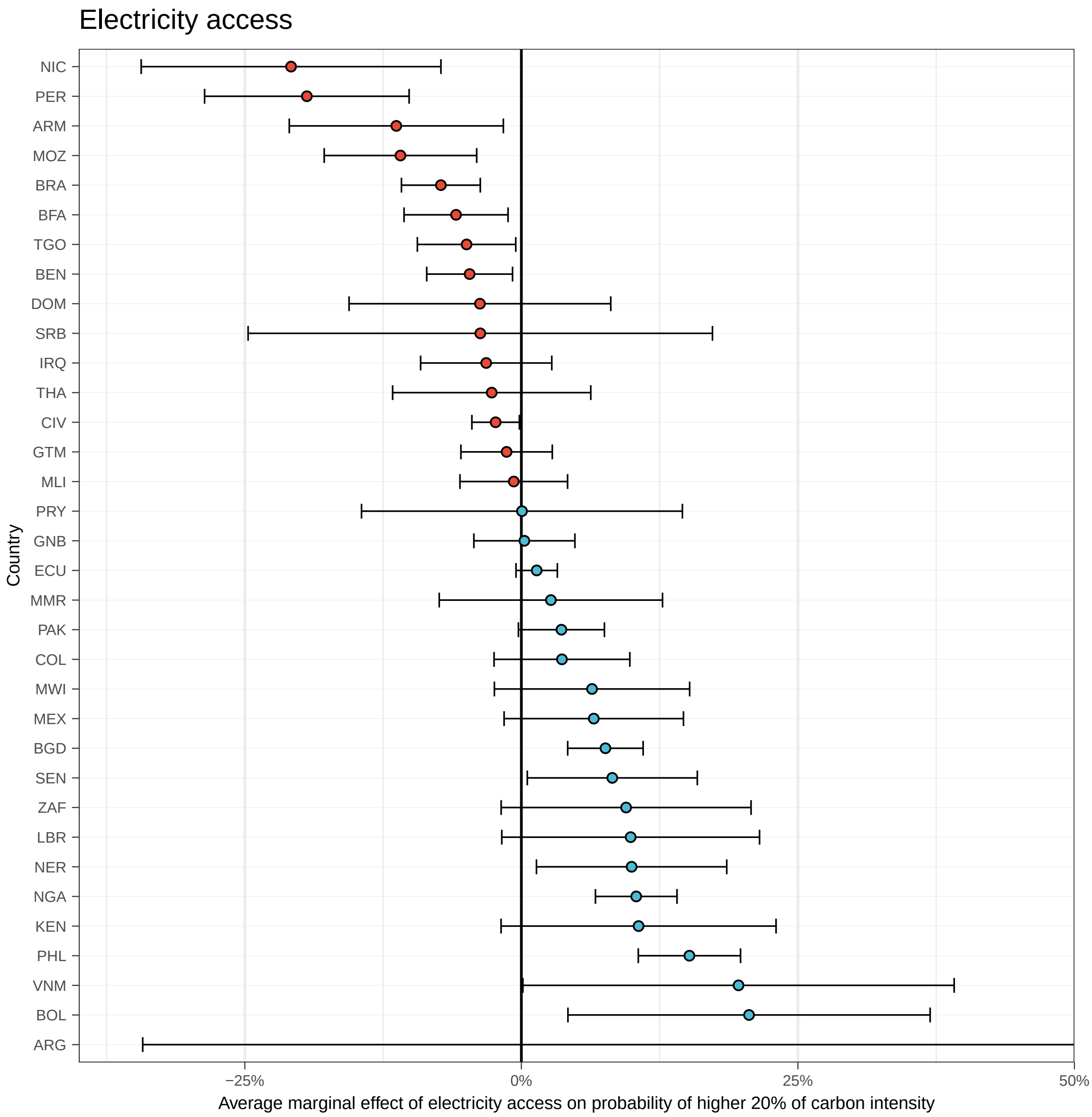
(B.10.4) Average marginal effects of urban citizenship

This figure shows average marginal effects of urban citizenship (in contrast to rural citizenship) on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



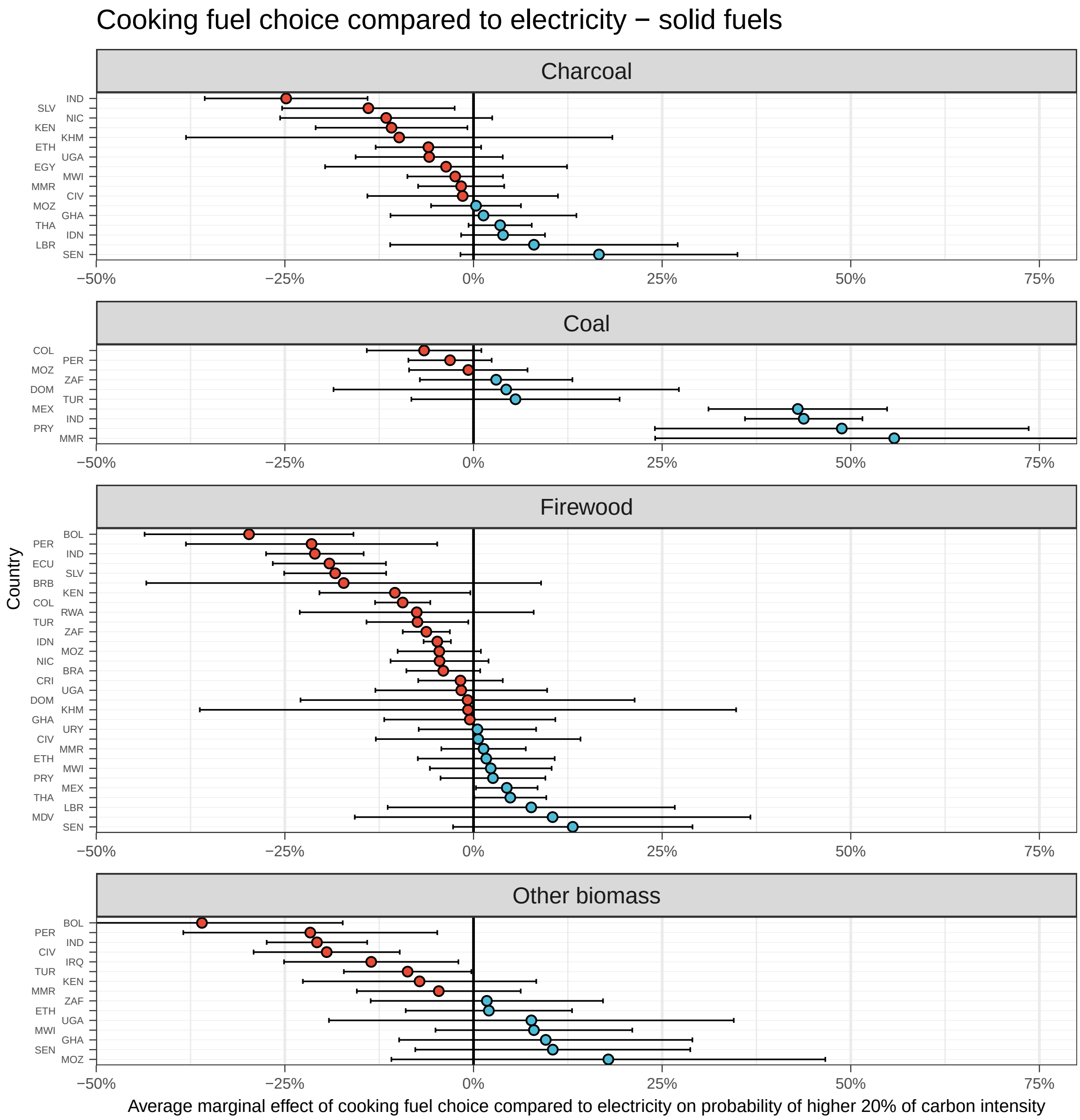
(B.10.5) Average marginal effects of household size

This figure shows average marginal effects of household size on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



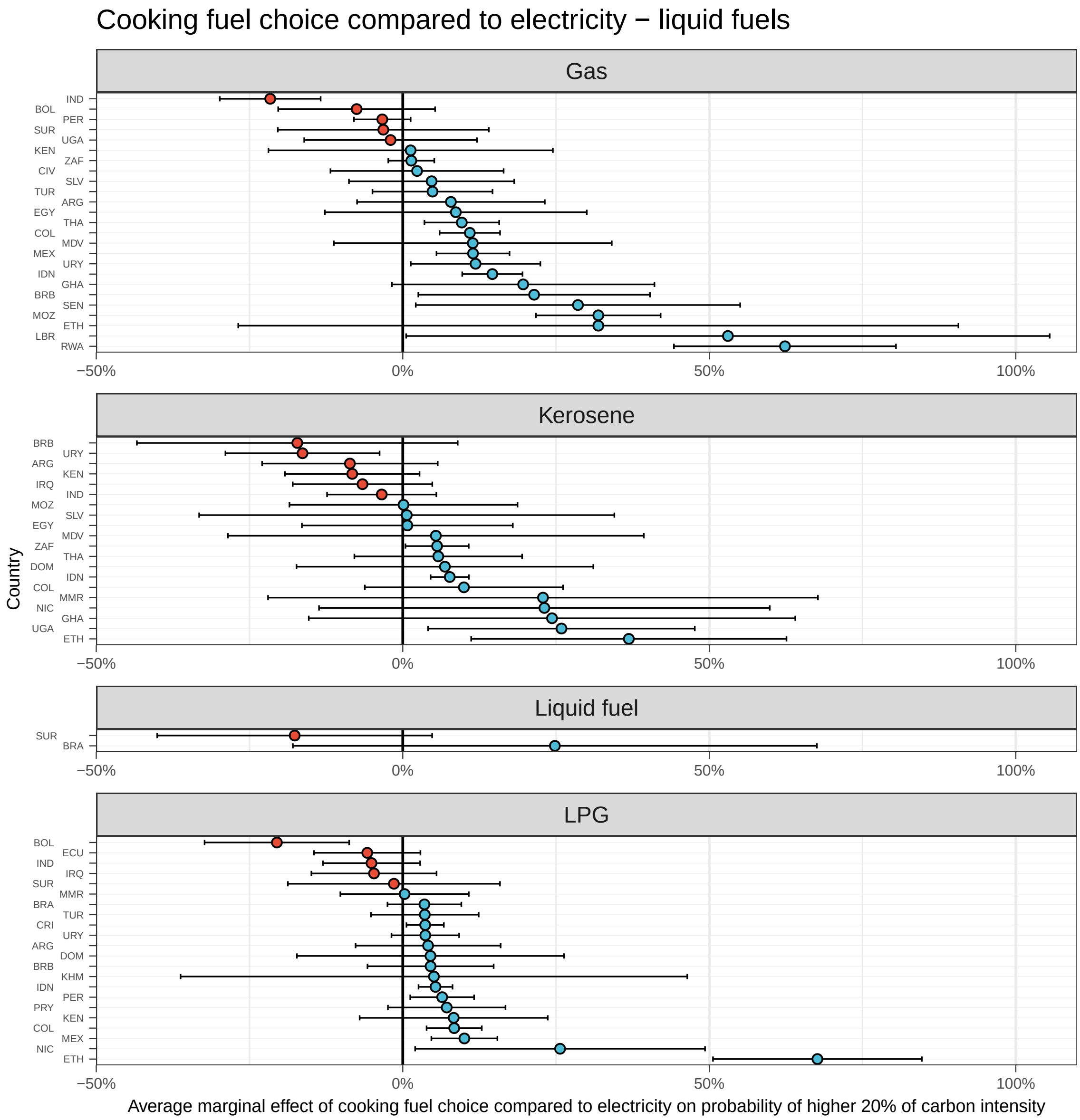
(B.10.6) Average marginal effects of electricity access

This figure shows average marginal effects of electricity access on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



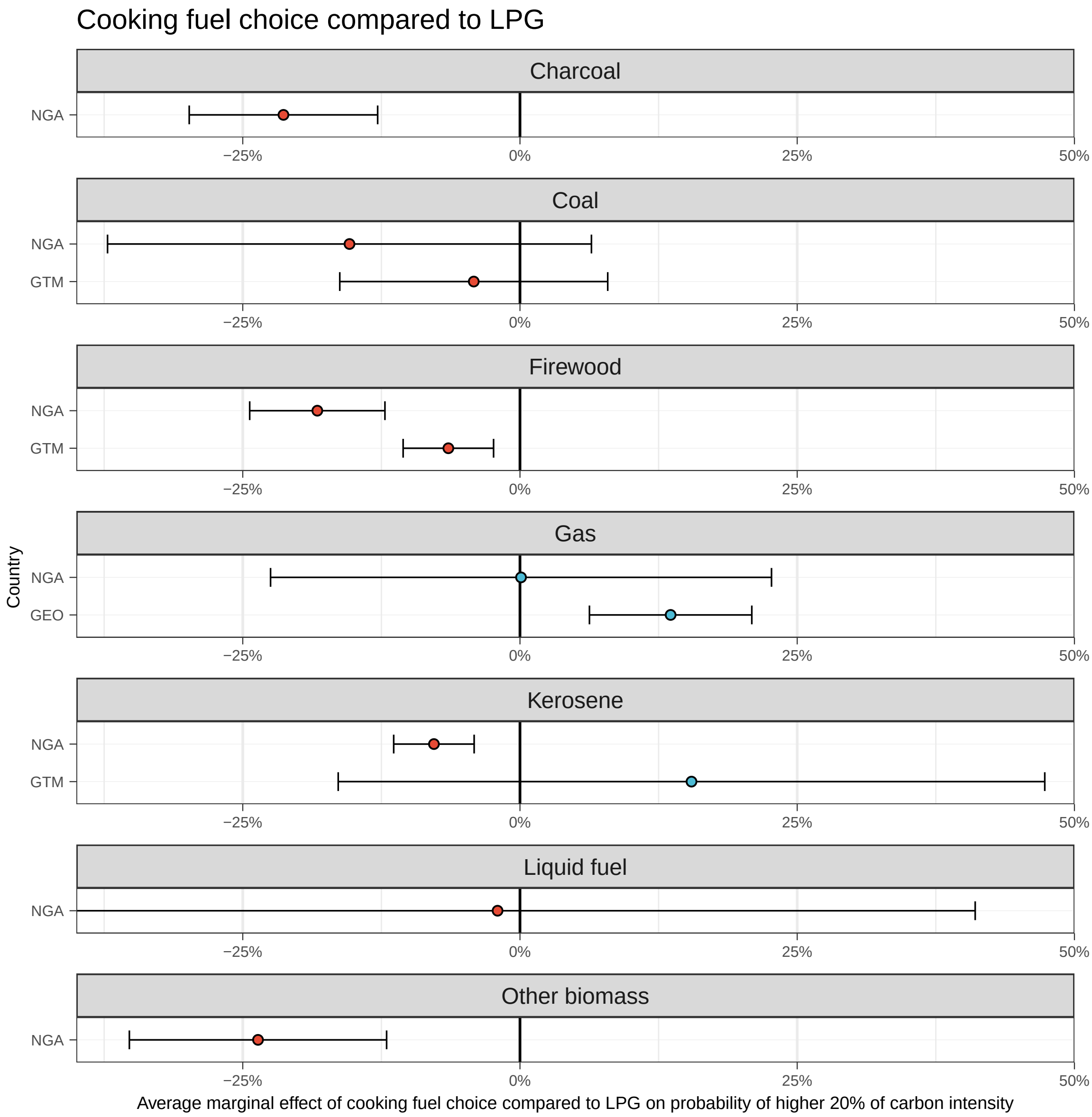
(B.10.7) Average marginal effects of cooking fuel choice - part A

This figure shows average marginal effects of using different cooking fuels (compared to using electricity) on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



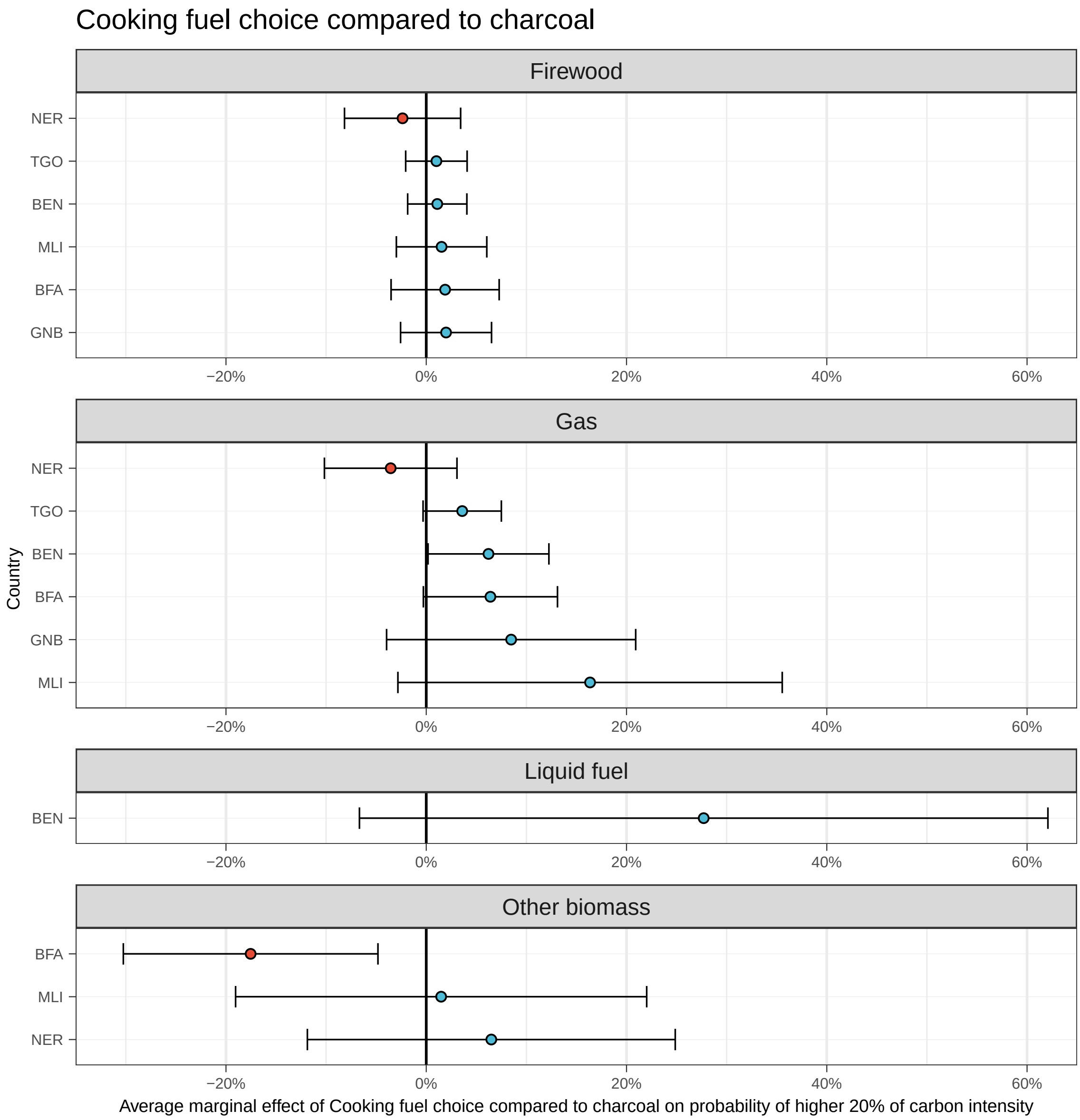
(B.10.8) Average marginal effects of cooking fuel choice - part B

This figure shows average marginal effects of using different cooking fuels (compared to using electricity) on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



(B.10.9) Average marginal effects of cooking fuel choice - part C

This figure shows average marginal effects of using different cooking fuels (compared to using LPG) on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.



(B.10.10) Average marginal effects of cooking fuel choice - part D

This figure shows average marginal effects of using different cooking fuels (compared to using charcoal) on the probability of consuming more carbon-intensively than 80% of households in each country. Estimates come from logit models (see Equation 12) including a rich set of control variables including total household expenditures. Control variables differ for different countries. Red points display negative estimates; blue points display positive estimates. Error bars display the 95%-confidence interval. Estimates are ordered in descending order.

Figure B.11: Overview of countries

1_Figures/Figures_Appendix/Figure_Maps_1.pdf

(B.11.1) Country clusters

This figure shows a map of all countries in our sample. Color refers to each country's cluster. See also Table C.11.

1_Figures/Figures_Appendix/Figure_Maps_2.pdf

(B.11.2) Goodness of fit (R^2) for each country

This figure shows a map of all countries in our sample. Color refers to the goodness of fit (R^2) for boosted regression tree models, fitted for each country.

1_Figures/Figures_Appendix/Figure_Maps_3.pdf

(B.11.3) Most important feature for each country

This figure shows a map of all countries in our sample. Color refers to the most important feature in boosted regression tree models, fitted for each country.

C Supplementary tables

Table C.1: Household budget surveys

Country	Survey name	Year	Sample size	Link
Argentina	Encuesta Nacional de Gastos de los Hogares	2017-2018	21,540	Link
Armenia	Integrated Living Conditions Survey	2017	7,776	Link
Austria	Konsumerhebung	2019-2020	7,162	Link
Australia	Household Expenditure, Income and Housing Survey	2015-2016	10,046	Link
Bangladesh	Household Income and Expenditure Survey	2010	12,240	Link
Barbados	Survey of Living Conditions	2016	2,434	Link
Benin	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	8,012	Link
Bolivia	Encuesta de Hogares	2019	11,859	Link
Brazil	Pesquisa de orcamentos familiares	2017-2018	57,889	Link
Burkina Faso	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	7,010	Link
Cambodia	Living Standards Measurement Study - Plus	2019-2020	1,206	Link
Canada	Survey of Household Spending	2017	4,012	Link
Chile	Encuesta de presupuestos familiares	2016-2017	15,237	Link
Colombia	Encuesta Nacional de Presupuestos de los Hogares	2016-2017	86,866	Link
Costa Rica	Encuesta Nacional de Ingresos y Gastos de los Hogares	2018	7,046	Link
Côte d'Ivoire	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	12,992	Link
Dominican Republic	Encuesta Nacional de Gastos e Ingresos de los Hogares	2018	8,884	Link
Ecuador	Encuesta Condiciones de Vida	2013-2014	28,263	Link
Egypt	Household Income, Expenditure and Consumption Survey	2017-2018	12,485	Link
El Salvador	Encuesta de Hogares de Propósitos Múltiples	2015	23,622	Link
Ethiopia	Socioeconomic Survey	2018-2019	6,767	Link
EU	Household Budget Survey	2015	275,427	Link
Georgia	Monitoring of Households	2019	13,247	Link
Ghana	Living Standards Survey 7	2016-2017	13,521	Link
Guatemala	Encuesta Nacional de Condiciones de Vida	2014	11,535	Link
Guinea-Bissau	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	5,351	Link
India	Socio-Economic Survey Sixty-Eighths round	2012	101,581	Link
Indonesia	Social Economic National Survey	2018	295,116	Link
Iraq	Household Socio Economic Survey	2012	24,994	Link
Israel	Household Budget Survey	2018	8,786	Link
Jordan	Household's Expenditures and Income Survey	2013	4,850	Link
Kenya	Integrated Household Budget Survey	2015-2016	21,714	Link
Liberia	Household Income Expenditure Survey	2016	8,332	Link
Malawi	Fifth Integrated Household Survey	2019-2020	11,374	Link
Maldives	Household Income and Expenditure Survey	2019	4,749	Link
Mali	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	6,602	Link
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	2020	74,158	Link
Mongolia	Household Socio-Economic Survey	2016	11,197	Link
Morocco	Enquête Nationale sur la Consommation et les Dépenses des ménages	2013-2014	15,970	Link
Myanmar	Poverty and Living Conditions Survey	2015	3,648	Link
Nicaragua	Encuesta de Medicion de Nivel de Vida	2014	6,850	Link
Niger	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	6,024	Link
Nigeria	Living Standards Survey	2018-2019	22,110	Link
Norway	Forbruksundersøkelsen	2012	3,363	Link
Pakistan	Household Integrated Economic Survey	2013-2014	23,886	Link
Paraguay	Encuesta de Ingresos y Gastos y de Condiciones de Vida	2011-2012	5,410	Link
Peru	Encuesta Nacional de Hogares	2019	34,542	Link
Philippines	Family Income and Expenditure Survey	2015	41,540	Link
Russia	Longitudinal Monitoring survey	2015	4,831	Link

Table C.1: Household budget surveys *(continued)*

Country	Survey name	Year	Sample size	Link
Rwanda	Integrated Household Living Conditions Survey	2016-2017	14,577	Link
Senegal	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	7,156	Link
Serbia	Household Buget Survey	2019	6,350	Link
South Africa	Living Conditions Survey	2014-2015	22,964	Link
Suriname	Survey of Living Conditions	2016-2017	2,025	Link
Switzerland	Haushaltsbudgeterhebung	2015–2017	9,955	Link
Taiwan	Survey of Family Income and Expenditure	2019	16,528	Link
Thailand	Household Socio-Economic Survey	2013	42,711	Link
Togo	Enquête Harmonisée sur le Conditions de Vie des Ménages	2018-2019	6,171	Link
Turkey	Household Budget Survey	2015	10,060	Link
Uganda	National Household Survey	2016-2017	15,627	Link
United Kingdom	Living Costs and Food Survey	2018-2019	5,425	Link
Uruguay	Encuesta Nacional de Gastos e Ingresos de los Hogares	2016-2017	6,888	Link
USA	Consumer Expenditure Surveys	2019	5,588	Link
Vietnam	Household Living Standards Survey	2012	9,378	Link

Note:
This table shows all household budget surveys used in this study. Column 'Year' refers to the year(s) when each survey was conducted. Column 'Sample size' refers to the number of individually-surveyed households in our final dataset, i.e., after data cleaning (see section A). Column 'Link' refers do additional online resources and information on data access for each dataset. Note that authors do not take any responsibility for changes on linked webpages.

Table C.2: Summary statistics

Country	Observations	Average household size	Urban population	Electricity access	Average household expenditures [USD]	Car ownership	Share of firewood or charcoal cons.
Argentina	21,540	3.19		99.8%	15,810	49%	5%
Armenia	7,776	3.63	66%	99.8%	4,779	32%	1%
Australia	10,027	2.58	63%		64,951		5%
Austria	7,162	2.23			38,002	77%	28%
Bangladesh	12,240	4.50	27%	55.2%	2,438	1%	39%
Barbados	2,434	2.62		94.7%	17,652	52%	0%
Belgium	6,133	2.31	96%		32,310		9%
Benin	8,012	5.21	47%	33.1%	2,690	3%	97%
Bolivia	11,859	3.34	69%	94.7%	4,089	17%	12%
Brazil	57,889	3.01	86%	99.5%	10,916	46%	3%
Bulgaria	2,964	2.37	71%		5,357		37%
Burkina Faso	7,010	6.51	31%	24.4%	2,660	4%	92%
Cambodia	1,206	4.34	27%		5,630	11%	73%
Canada	4,012	2.32			48,762	86%	0%
Chile	15,237	3.29			19,014		11%
Colombia	86,866	3.35	79%	98.3%	6,856	14%	9%
Costa Rica	7,046	3.24	71%	99.7%	11,830	45%	5%
Côte d'Ivoire	12,992	4.48	52%	64.1%	3,247	3%	77%
Croatia	2,029	2.89	59%		11,890		51%
Cyprus	2,876	2.70	74%		26,575		21%
Czechia	2,905	2.22	67%		11,098		22%
Denmark	2,205	2.12	67%		37,759		21%
Dominican Republic	8,884	3.21	81%	97.5%	7,549	21%	7%
Ecuador	28,263	3.68	69%	90.5%	6,831	19%	5%
Egypt	12,485	4.17	46%	99.5%	2,449	7%	0%
El Salvador	23,622	3.67	64%	95.7%	5,758	15%	12%
Estonia	3,395	2.24	51%		11,994		33%
Ethiopia	6,767	4.48	32%	55.9%	1,167	1%	96%
Finland	3,673	2.02	71%		31,618		43%
France	16,978	2.23	69%		26,865		0%
Georgia	13,247	2.44	61%	100%	2,436	29%	5%
Germany	52,388	2.00	90%		28,683		0%
Ghana	13,521	3.91	56%	83.1%	2,380	4%	83%
Greece	6,140	2.58	72%		19,219		28%
Guatemala	11,535	4.77	54%	81%	5,677	17%	70%
Guinea-Bissau	5,351	8.18	47%	21.7%	3,691	3%	99%
Hungary	7,183	2.34	56%		8,385		42%

Table C.2: Summary statistics *(continued)*

Country	Observations	Average household size	Urban population	Electricity access	Average household expenditures [USD]	Car ownership	Share of firewood or charcoal cons.
India	101,581	4.43	31%	79.9%	1,612	4%	63%
Indonesia	295,116	3.77	55%	98.5%	2,838	11%	29%
Iraq	24,994	6.73	72%	99.3%	14,006	35%	3%
Ireland	6,837	2.73	65%		33,816		31%
Israel	8,786	3.28	90%		39,035	72%	0%
Italy	14,636	2.37	82%		23,955		15%
Jordan	4,850	5.11	83%		11,973	51%	0%
Kenya	21,714	3.98	44%	56.4%	2,468		82%
Latvia	3,844	2.37	56%		10,195		0%
Liberia	8,332	4.27	52%	16.7%	2,568	2%	99%
Lithuania	3,441	2.15	47%		8,884		33%
Luxembourg	3,163	2.42	81%		50,165		0%
Malawi	11,374	4.40	16%	10.7%	707	2%	99%
Maldives	4,749	5.19			20,199	5%	0%
Mali	6,602	7.14	28%	27.5%	3,458	4%	99%
Mexico	74,158	3.61	77%	99.5%	5,928	38%	16%
Mongolia	11,197	3.58	66%		5,939		44%
Morocco	15,970	4.74	65%		7,374		21%
Mozambique	11,335	5.01	31%	25.3%	2,872	1%	96%
Myanmar (Burma)	3,648	4.53	29%	63%	2,347	4%	88%
Netherlands	14,407	2.19	90%		34,292		1%
Nicaragua	6,850	4.38	60%	86.8%	4,799	8%	51%
Niger	6,024	5.96	17%	15.7%	1,901	2%	97%
Nigeria	22,110	5.08	40%	63.4%	3,013	8%	70%
Norway	3,363	2.77	82%		53,131	88%	0%
Pakistan	23,886	6.32	37%	90.1%	3,491		25%
Paraguay	5,410	3.90	61%	97.8%	7,393	25%	29%
Peru	34,542	3.56	77%	95.6%	4,673	12%	15%
Philippines	41,540	4.60	44%	91.1%	4,468	7%	45%
Poland	37,115	2.80	64%		12,779		6%
Portugal	11,392	2.53	73%		17,731		9%
Romania	30,605	2.66	58%		5,094		9%
Russia	4,831	2.60			7,511	41%	3%
Rwanda	14,577	4.39	19%		1,262	1%	41%
Senegal	7,156	8.91	53%	63.7%	6,705	5%	86%
Serbia	6,350	2.68	62%	99.9%	7,608	91%	14%
Slovakia	4,785	2.93	71%		12,839		19%
South Africa	22,964	3.53	70%	92.7%	6,958	27%	10%
Spain	22,127	2.50	75%		22,569		0%
Suriname	2,025	3.39	72%		7,589	38%	0%
Sweden	2,871	2.13	45%		29,741		0%
Switzerland	9,955	2.14			76,279	77%	0%

Table C.2: Summary statistics *(continued)*

Country	Observations	Average household size	Urban population	Electricity access	Average household expenditures [USD]	Car ownership	Share of firewood or charcoal cons.
Taiwan	16,528	3.02			20,687	61%	0%
Thailand	42,711	3.04	36%	99.8%	3,747	14%	26%
Togo	6,171	4.23	47%	51.8%	2,381	3%	92%
Turkey	10,060	3.64	70%		9,986	39%	4%
Uganda	15,627	4.82	28%	39.2%	1,262	3%	95%
United Kingdom	5,425	2.37	77%		35,305	75%	1%
United States	5,588	2.44	94%		43,740		0%
Uruguay	6,888	2.82	83%	99.7%	21,058	46%	13%
Vietnam	9,378	3.84	30%	97.8%	2,362	1%	15%

Note:
This table shows summary statistics for households in our sample. All values (except observations) are household-weighted averages. Column 'Share of firewood or charcoal cons.' refers to the share of households that report positive expenditures on firewood, charcoal, and other biomass, or that report firewood, charcoal, or other biomass to be their main cooking fuel.

Table C.3: Average household expenditures and average energy expenditure shares per expenditure quintile

	Average household expenditures [USD]						Average energy expenditure shares					
		Expenditure quintile						Expenditure quintile				
Country	All	EQ1	EQ2	EQ3	EQ4	EQ5	All	EQ1	EQ2	EQ3	EQ4	EQ5
Argentina	15,810	6,006	10,101	13,399	19,348	30,208	14%	17%	15%	14%	13%	10%
Armenia	4,779	1,788	2,698	3,410	4,486	11,516	19%	24%	21%	20%	18%	14%
Australia	64,951	29,364	44,944	59,584	75,858	115,036	7%	10%	8%	6%	5%	4%
Austria	38,002	22,388	29,851	34,946	41,378	61,452	10%	14%	11%	10%	9%	6%
Bangladesh	2,438	1,081	1,599	2,053	2,785	4,670	4%	4%	4%	4%	4%	4%
Barbados	17,652	7,207	12,755	16,958	19,869	31,430	13%	13%	13%	14%	13%	11%
Belgium	32,310	22,621	28,847	30,183	33,559	46,362	12%	14%	12%	12%	11%	8%
Benin	2,690	992	1,750	2,461	3,389	4,862	8%	6%	7%	8%	9%	11%
Bolivia	4,089	1,933	3,172	4,025	4,860	6,455	6%	7%	6%	6%	6%	6%
Brazil	10,916	2,581	5,127	7,755	11,913	27,207	14%	22%	15%	14%	12%	9%
Bulgaria	5,357	3,192	3,993	4,659	6,346	8,599	18%	20%	19%	19%	18%	15%
Burkina Faso	2,660	857	1,480	2,083	3,204	5,685	7%	4%	5%	6%	8%	11%
Cambodia	5,630	2,315	3,658	4,827	6,704	10,646	10%	12%	11%	10%	9%	9%
Canada	48,762	27,580	39,736	51,168	57,846	67,509	7%	9%	7%	7%	6%	5%
Chile	19,014	7,027	11,788	15,847	21,794	38,639	9%	13%	10%	9%	8%	6%
Colombia	6,856	1,573	3,032	4,480	7,131	18,065	9%	12%	10%	9%	7%	5%
Costa Rica	11,830	4,760	7,311	9,620	13,286	24,185	10%	13%	11%	10%	10%	8%
Côte d'Ivoire	3,247	1,429	2,389	3,226	3,988	5,203	6%	5%	6%	6%	6%	7%
Croatia	11,890	7,477	9,738	11,308	13,565	17,379	18%	21%	20%	18%	17%	15%
Cyprus	26,575	15,161	22,006	25,997	32,022	37,715	13%	16%	15%	13%	12%	11%
Czechia	11,098	8,778	10,304	10,431	11,321	14,666	18%	20%	19%	19%	17%	15%
Denmark	37,759	30,738	35,130	33,241	38,592	51,136	12%	13%	12%	12%	11%	9%
Dominican Republic	7,549	4,028	5,720	6,941	8,312	12,746	10%	9%	9%	9%	9%	12%
Ecuador	6,831	2,598	4,384	5,672	7,473	14,031	7%	8%	6%	6%	6%	7%
Egypt	2,449	1,818	2,254	2,503	2,679	2,992	6%	6%	6%	6%	6%	7%
El Salvador	5,758	1,288	2,977	4,741	6,945	12,837	20%	26%	23%	20%	17%	14%
Estonia	11,994	5,508	8,135	10,775	13,514	22,065	15%	19%	17%	15%	14%	11%
Ethiopia	1,167	315	637	894	1,507	2,484	3%	1%	1%	2%	5%	5%
Finland	31,618	22,870	26,434	29,418	32,624	46,756	8%	10%	9%	8%	7%	6%
France	26,865	16,685	22,878	26,440	29,591	38,733	11%	13%	12%	11%	10%	8%
Georgia	2,436	1,200	1,877	2,259	2,805	4,039	15%	16%	16%	16%	15%	14%
Germany	28,683	21,286	24,135	26,800	30,032	41,165	14%	17%	15%	14%	13%	11%
Ghana	2,380	1,152	1,939	2,413	2,941	3,456	8%	6%	8%	8%	9%	9%
Greece	19,219	11,094	14,308	17,392	20,706	32,600	14%	17%	16%	14%	12%	10%
Guatemala	5,677	2,573	3,998	5,079	6,480	10,264	16%	20%	16%	15%	15%	14%
Guinea-Bissau	3,691	1,509	2,511	3,345	4,414	6,680	4%	2%	2%	3%	5%	8%
Hungary	8,385	5,510	7,127	8,031	9,418	11,844	20%	22%	21%	21%	20%	17%
India	1,612	766	1,039	1,324	1,832	3,096	8%	7%	8%	9%	10%	9%
Indonesia	2,838	1,098	1,813	2,483	3,404	5,389	12%	14%	12%	12%	11%	11%
Iraq	14,006	5,814	9,093	11,797	15,700	27,626	9%	12%	10%	9%	8%	6%
Ireland	33,816	20,940	28,039	33,885	39,209	47,012	13%	16%	15%	13%	13%	10%
Israel	39,035	19,942	29,931	37,966	46,088	61,265	8%	10%	8%	7%	7%	5%
Italy	23,955	12,955	19,094	23,242	28,164	36,327	14%	19%	16%	14%	13%	10%
Jordan	11,973	7,249	9,500	11,219	13,962	17,945	18%	15%	16%	18%	19%	20%
Kenya	2,468	680	1,392	2,090	2,914	5,264	6%	6%	6%	7%	6%	6%
Latvia	10,195	5,082	6,886	8,617	11,189	19,247	16%	18%	18%	17%	16%	13%
Liberia	2,568	877	1,691	2,488	3,410	4,373	3%	3%	2%	3%	4%	5%
Lithuania	8,884	5,299	6,510	7,752	10,515	14,345	18%	18%	18%	19%	19%	16%
Luxembourg	50,165	32,990	40,936	50,079	57,996	68,841	9%	12%	9%	8%	8%	6%
Malawi	707	165	358	531	812	1,671	2%	0%	1%	2%	4%	6%
Maldives	20,199	10,578	15,915	19,813	24,859	29,864	7%	10%	8%	7%	5%	4%
Mali	3,458	1,197	2,035	2,991	4,428	6,640	6%	4%	6%	6%	8%	8%
Mexico	5,928	2,352	3,954	5,158	6,696	11,481	11%	9%	10%	11%	12%	11%
Mongolia	5,939	2,961	4,183	5,131	6,430	10,994	10%	10%	11%	10%	10%	7%

Table C.3: Average household expenditures and average energy expenditure shares per expenditure quintile *(continued)*

Country	All	EQ1	EQ2	EQ3	EQ4	EQ5	All	EQ1	EQ2	EQ3	EQ4	EQ5
Morocco	7,374	3,913	5,362	6,458	8,158	12,980	8%	10%	8%	7%	7%	7%
Mozambique	2,872	259	826	1,686	3,521	8,070	3%	1%	1%	2%	4%	8%
Myanmar (Burma)	2,347	1,077	1,592	2,078	2,726	4,267	5%	5%	5%	5%	6%	6%
Netherlands	34,292	28,234	32,071	31,728	34,389	45,040	10%	12%	11%	10%	9%	8%
Nicaragua	4,799	1,405	2,549	3,596	5,244	11,210	6%	4%	5%	6%	7%	8%
Niger	1,901	620	1,109	1,505	2,107	4,164	3%	1%	1%	2%	3%	7%
Nigeria	3,013	1,387	2,331	3,027	3,830	4,490	5%	4%	4%	5%	6%	6%
Norway	53,131	28,936	41,880	51,002	60,249	83,632	10%	14%	12%	10%	9%	7%
Pakistan	3,491	2,108	2,715	3,105	3,805	5,721	9%	7%	8%	10%	10%	11%
Paraguay	7,393	2,467	4,802	6,952	9,083	13,666	10%	10%	11%	10%	11%	10%
Peru	4,673	1,602	3,122	4,351	5,615	8,674	8%	9%	9%	8%	8%	7%
Philippines	4,468	1,797	2,725	3,826	5,347	8,644	6%	4%	5%	6%	7%	7%
Poland	12,779	7,052	9,043	10,500	13,250	24,054	15%	16%	17%	16%	14%	10%
Portugal	17,731	8,965	13,050	16,205	20,326	30,114	17%	22%	19%	17%	15%	12%
Romania	5,094	3,385	4,236	4,962	5,601	7,287	17%	14%	17%	18%	18%	17%
Russia	7,511	3,519	5,384	6,632	8,142	13,882	2%	2%	2%	2%	2%	2%
Rwanda	1,262	409	674	921	1,369	2,934	3%	1%	2%	3%	4%	6%
Senegal	6,705	3,068	5,046	6,842	8,208	10,363	5%	3%	4%	5%	6%	7%
Serbia	7,608	4,582	6,653	7,751	8,867	10,186	14%	13%	15%	14%	15%	14%
Slovakia	12,839	8,789	10,999	11,995	13,491	18,926	20%	23%	21%	21%	18%	14%
South Africa	6,958	1,759	2,870	3,973	6,710	19,481	11%	11%	10%	11%	12%	12%
Spain	22,569	11,705	17,656	22,096	27,275	34,113	12%	14%	13%	12%	11%	9%
Suriname	7,589	2,945	5,059	6,845	8,984	14,128	6%	8%	7%	6%	5%	4%
Sweden	29,741	21,182	25,923	29,313	31,219	41,079	10%	13%	12%	11%	9%	8%
Switzerland	76,279	59,450	68,911	74,065	80,506	98,479	4%	5%	4%	4%	4%	3%
Taiwan	20,687	13,196	17,886	20,624	23,589	28,141	10%	11%	11%	11%	10%	9%
Thailand	3,747	1,037	1,872	2,997	4,746	8,084	20%	20%	23%	23%	19%	14%
Togo	2,381	818	1,539	2,281	3,153	4,116	8%	4%	7%	8%	9%	10%
Turkey	9,986	4,952	6,964	8,971	11,133	17,908	11%	11%	12%	12%	12%	10%
Uganda	1,262	288	656	1,036	1,607	2,724	5%	4%	3%	5%	6%	7%
United Kingdom	35,305	15,963	25,049	32,867	40,587	62,085	10%	12%	12%	10%	9%	7%
United States	43,740	24,289	33,982	41,692	48,659	70,120	10%	13%	12%	10%	9%	6%
Uruguay	21,058	8,145	13,362	18,386	24,910	40,504	10%	13%	11%	9%	8%	7%
Vietnam	2,362	762	1,435	2,072	2,975	4,566	5%	5%	5%	5%	5%	4%

Note:

This table shows average household expenditures and average energy expenditure shares for households in our sample. We estimate household-weighted averages for the whole population and per expenditure quintile.

Table C.4: Share of households using cooking fuels

	Solid fuels					Liquid or gaseous fuels					Electricity				
	Expenditure quintile					Expenditure quintile					Expenditure quintile				
Country	EQ1	EQ2	EQ3	EQ4	EQ5	EQ1	EQ2	EQ3	EQ4	EQ5	EQ1	EQ2	EQ3	EQ4	EQ5
Argentina	-	-	-	-	-	99%	99%	99%	98%	96%	1%	0%	1%	2%	4%
Barbados	0%	0%	-	-	-	89%	95%	94%	94%	88%	4%	4%	5%	5%	11%
Benin	100%	100%	99%	96%	77%	-	0%	1%	3%	23%	-	-	-	-	-
Bolivia	36%	12%	6%	3%	2%	63%	87%	92%	93%	89%	-	0%	0%	0%	1%
Brazil	3%	1%	0%	0%	0%	95%	98%	98%	99%	98%	0%	1%	1%	1%	1%
Burkina Faso	99%	100%	98%	89%	43%	0%	0%	1%	11%	56%	-	-	-	-	-
Cambodia	82%	59%	59%	44%	24%	17%	41%	41%	54%	74%	1%	0%	1%	0%	2%
Colombia	28%	10%	4%	3%	1%	68%	86%	92%	92%	92%	3%	3%	3%	3%	5%
Costa Rica	11%	4%	3%	2%	1%	52%	54%	47%	44%	29%	36%	41%	50%	54%	69%
Côte d'Ivoire	97%	92%	73%	49%	27%	2%	8%	26%	49%	68%	-	-	-	-	0%
Dominican Republic	10%	4%	3%	2%	1%	89%	94%	93%	92%	91%	0%	-	0%	0%	0%
Ecuador	15%	4%	2%	1%	0%	80%	94%	95%	96%	95%	0%	0%	0%	0%	1%
Egypt	0%	0%	0%	0%	-	100%	100%	100%	100%	100%	0%	0%	-	0%	0%
El Salvador	32%	12%	7%	3%	2%	62%	87%	91%	95%	88%	0%	0%	1%	1%	4%
Ethiopia	99%	99%	98%	90%	64%	0%	1%	0%	1%	2%	0%	0%	1%	8%	29%
Georgia	-	-	-	-	-	95%	97%	98%	98%	99%	-	-	-	-	-
Ghana	97%	87%	70%	55%	31%	2%	11%	25%	35%	51%	-	0%	0%	0%	1%
Guatemala	98%	92%	75%	58%	28%	1%	7%	23%	41%	68%	-	-	-	-	-
Guinea-Bissau	100%	99%	98%	99%	93%	-	0%	0%	1%	6%	-	-	-	-	-
India	92%	84%	70%	41%	9%	2%	9%	25%	56%	79%	0%	0%	0%	0%	0%
Indonesia	42%	21%	12%	6%	2%	57%	78%	87%	92%	92%	0%	0%	0%	1%	1%
Iraq	2%	0%	0%	0%	0%	98%	99%	100%	99%	99%	1%	1%	0%	1%	0%
Jordan	0%	0%	0%	-	-	100%	100%	100%	100%	100%	-	-	-	-	-
Kenya	98%	94%	79%	52%	24%	1%	5%	18%	44%	70%	0%	0%	1%	2%	2%
Liberia	100%	99%	99%	99%	98%	0%	0%	-	0%	0%	0%	-	-	0%	0%
Malawi	100%	100%	100%	100%	95%	-	-	-	-	-	-	-	0%	0%	5%
Maldives	2%	0%	0%	-	-	96%	96%	98%	97%	95%	0%	1%	1%	1%	2%
Mali	100%	100%	100%	99%	94%	-	-	-	1%	5%	-	-	-	-	-
Mexico	43%	17%	9%	4%	2%	56%	81%	90%	94%	95%	1%	1%	1%	1%	2%
Mozambique	100%	100%	99%	99%	85%	0%	0%	0%	1%	11%	-	0%	0%	1%	4%
Myanmar (Burma)	95%	90%	85%	78%	66%	1%	0%	1%	1%	3%	3%	10%	14%	19%	30%
Nicaragua	94%	75%	49%	28%	10%	5%	24%	50%	70%	88%	0%	0%	1%	1%	0%
Niger	98%	99%	99%	98%	81%	-	-	0%	1%	18%	-	-	-	-	-
Nigeria	98%	91%	72%	47%	19%	1%	9%	27%	52%	77%	-	-	-	-	-
Paraguay	83%	56%	28%	17%	5%	12%	38%	65%	74%	81%	2%	4%	5%	8%	10%
Peru	31%	10%	4%	2%	0%	60%	85%	89%	87%	76%	1%	3%	5%	11%	21%
Rwanda	-	-	-	-	0%	-	-	-	0%	5%	99%	99%	99%	100%	94%
Senegal	98%	90%	71%	48%	18%	2%	10%	29%	51%	79%	-	-	-	0%	0%
South Africa	28%	13%	6%	2%	0%	8%	9%	9%	6%	8%	63%	77%	85%	91%	92%
Suriname	-	-	-	-	-	99%	98%	99%	97%	96%	0%	2%	0%	2%	2%
Thailand	56%	33%	16%	8%	4%	38%	63%	77%	76%	67%	1%	1%	2%	4%	7%
Togo	100%	99%	96%	90%	62%	-	0%	3%	9%	36%	-	-	-	-	-
Turkey	16%	3%	1%	1%	0%	80%	96%	98%	98%	98%	3%	1%	0%	1%	2%
Uganda	96%	98%	97%	95%	85%	0%	0%	0%	1%	6%	0%	0%	0%	1%	2%
Uruguay	3%	1%	1%	1%	0%	93%	96%	96%	94%	90%	3%	3%	3%	6%	10%

Note:
This table shows the share of households using different cooking fuels, such as solid fuels (e.g., firewood, charcoal, coal, biomass), liquid fuels (e.g., LPG, natural gas, kerosene), or electricity over expenditure quintiles.

Table C.5: Share of households using lighting fuels

Country	Kerosene EQ1	Kerosene EQ2	Kerosene EQ3	Kerosene EQ4	Kerosene EQ5	Electricity EQ1	Electricity EQ2	Electricity EQ3	Electricity EQ4	Electricity EQ5	Other lighting fuels EQ1	Other lighting fuels EQ2	Other lighting fuels EQ3	Other lighting fuels EQ4	Other lighting fuels EQ5
Barbados	1%	1%	1%	0%	-	88%	95%	97%	97%	97%	3%	3%	2%	2%	1%
Benin	1%	0%	1%	0%	1%	20%	30%	42%	60%	74%	80%	70%	58%	40%	25%
Burkina Faso	0%	0%	0%	0%	0%	29%	38%	44%	66%	91%	65%	59%	52%	30%	8%
Cambodia	2%	1%	-	-	1%	85%	94%	96%	96%	98%	12%	5%	4%	4%	1%
Costa Rica	-	-	-	-	-	99%	100%	100%	100%	100%	-	-	-	-	-
Côte d'Ivoire	0%	0%	0%	0%	0%	60%	74%	84%	90%	95%	37%	24%	15%	9%	4%
Dominican Republic	2%	2%	1%	1%	0%	96%	97%	98%	98%	99%	2%	1%	1%	1%	0%
Ecuador	-	-	-	-	-	95%	99%	99%	100%	100%	-	-	-	-	-
Egypt	0%	0%	0%	0%	1%	99%	100%	99%	99%	99%	0%	0%	0%	0%	0%
El Salvador	4%	1%	0%	0%	0%	87%	96%	98%	99%	99%	9%	3%	2%	1%	1%
Ethiopia	30%	27%	23%	14%	3%	30%	43%	48%	68%	90%	41%	29%	29%	18%	7%
Ghana	1%	1%	1%	1%	-	60%	80%	88%	92%	96%	36%	17%	11%	7%	4%
Guatemala	-	-	-	-	-	58%	82%	89%	96%	97%	37%	15%	9%	4%	2%
Guinea-Bissau	1%	0%	0%	0%	0%	43%	46%	49%	58%	72%	48%	48%	47%	37%	25%
India	48%	28%	15%	6%	2%	51%	72%	85%	94%	98%	0%	0%	0%	0%	0%
Indonesia	-	-	-	-	-	96%	98%	99%	100%	100%	-	-	-	-	-
Iraq	1%	0%	0%	0%	0%	99%	100%	100%	100%	100%	0%	-	-	-	-
Kenya	56%	53%	37%	20%	9%	23%	38%	57%	75%	88%	18%	8%	5%	4%	2%
Liberia	-	0%	0%	-	-	0%	3%	9%	20%	38%	98%	96%	90%	78%	59%
Malawi	1%	1%	0%	0%	0%	0%	1%	3%	10%	39%	97%	97%	95%	88%	58%
Mali	1%	1%	0%	0%	0%	61%	66%	68%	80%	94%	27%	26%	26%	18%	5%
Mozambique	11%	14%	17%	17%	8%	2%	5%	14%	39%	74%	87%	82%	68%	43%	18%
Myanmar (Burma)	13%	5%	4%	5%	2%	46%	55%	61%	69%	77%	41%	39%	35%	27%	21%
Nicaragua	14%	4%	3%	2%	0%	62%	85%	92%	96%	99%	-	-	-	-	-
Niger	1%	0%	0%	0%	0%	3%	6%	13%	25%	58%	95%	94%	87%	74%	41%
Peru	1%	0%	0%	0%	0%	86%	96%	98%	99%	99%	-	-	-	-	-
Rwanda	-	-	-	-	-	79%	83%	83%	85%	92%	20%	16%	16%	14%	8%
Senegal	1%	1%	0%	0%	0%	40%	61%	83%	91%	96%	55%	35%	14%	8%	3%
South Africa	3%	2%	2%	1%	0%	85%	89%	92%	96%	99%	12%	8%	6%	3%	0%
Suriname	-	-	-	-	-	89%	96%	99%	99%	99%	6%	2%	1%	0%	1%
Togo	0%	0%	1%	0%	0%	13%	36%	62%	79%	89%	85%	63%	37%	19%	10%
Uganda	44%	50%	40%	24%	10%	14%	21%	33%	52%	76%	8%	3%	3%	5%	4%
Uruguay	0%	0%	-	-	-	99%	100%	100%	100%	100%	1%	0%	0%	0%	0%
Vietnam	5%	1%	0%	0%	0%	94%	99%	100%	100%	100%	-	-	-	-	-

Note:
This table shows the share of households using different lighting fuels over expenditure quintiles.

Table C.6: Share of households possessing different assets

Country	Car All	Car EQ1	Car EQ5	TV All	TV EQ1	TV EQ5	Refrigerator All	Refrigerator EQ1	Refrigerator EQ5	AC All	AC EQ1	AC EQ5	Washing machine All	Washing machine EQ1	Washing machine EQ5
Argentina	49%	26%	66%	97%	96%	97%	98%	95%	99%	53%	33%	72%	87%	81%	87%
Armenia	32%	24%	41%	99%	99%	99%	96%	94%	98%	8%	4%	14%	92%	91%	95%
Austria	77%	70%	82%	94%	94%	93%	99%	99%	99%	4%	2%	6%	95%	95%	95%
Bangladesh	1%	0%	2%	36%	9%	71%	12%	0%	44%	-	-	-	0%	0%	1%
Barbados	52%	21%	75%	49%	34%	61%	94%	84%	97%	8%	2%	18%	75%	60%	86%
Benin	3%	0%	12%	23%	3%	52%	4%	0%	14%	0%	0%	1%	0%	0%	1%
Bolivia	17%	5%	31%	84%	61%	92%	61%	28%	77%	10%	2%	22%	18%	2%	40%
Brazil	46%	17%	76%	97%	94%	98%	98%	96%	99%	20%	6%	42%	65%	38%	87%
Burkina Faso	4%	0%	17%	30%	3%	78%	9%	0%	38%	2%	0%	8%	0%	0%	0%
Cambodia	11%	2%	34%	-	-	-	-	-	-	-	-	-	-	-	-
Canada	86%	74%	94%	74%	75%	72%	-	-	-	-	-	-	-	-	-
Colombia	14%	1%	39%	92%	81%	97%	83%	66%	92%	4%	1%	7%	61%	34%	82%
Costa Rica	45%	19%	74%	97%	95%	98%	96%	92%	98%	-	-	-	-	-	-
Côte d'Ivoire	3%	0%	10%	45%	15%	70%	15%	1%	35%	2%	0%	9%	2%	1%	5%
Dominican Republic	21%	6%	45%	87%	83%	89%	83%	74%	87%	14%	2%	37%	80%	72%	84%
Ecuador	19%	2%	52%	91%	78%	98%	80%	56%	93%	6%	0%	17%	45%	15%	71%
Egypt	7%	1%	21%	96%	95%	97%	97%	95%	98%	12%	4%	29%	95%	95%	94%
El Salvador	15%	1%	40%	87%	68%	95%	67%	36%	84%	1%	0%	5%	17%	2%	44%
Ethiopia	1%	0%	4%	18%	1%	51%	7%	0%	25%	-	-	-	-	-	-
Georgia	29%	18%	37%	96%	94%	95%	91%	85%	93%	8%	1%	17%	74%	61%	83%
Ghana	4%	1%	9%	64%	31%	85%	36%	7%	57%	1%	0%	3%	1%	0%	3%
Guatemala	17%	2%	44%	71%	34%	92%	5%	0%	16%	-	-	-	11%	0%	36%
Guinea-Bissau	3%	0%	12%	26%	5%	59%	13%	0%	40%	1%	0%	2%	0%	0%	1%
India	4%	1%	15%	59%	23%	82%	20%	1%	58%	12%	2%	30%	9%	0%	32%
Indonesia	11%	1%	36%	14%	2%	38%	57%	25%	80%	8%	0%	29%	-	-	-
Iraq	35%	17%	62%	-	-	-	92%	83%	98%	41%	21%	59%	69%	41%	89%
Israel	72%	53%	82%	88%	76%	93%	100%	100%	100%	93%	89%	97%	96%	97%	94%
Jordan	51%	27%	70%	99%	98%	100%	98%	96%	98%	20%	9%	39%	97%	95%	97%
Liberia	2%	0%	6%	18%	1%	43%	4%	0%	15%	0%	0%	1%	-	-	-
Malawi	2%	0%	6%	11%	0%	38%	4%	0%	19%	0%	0%	0%	0%	0%	0%
Maldives	5%	2%	8%	87%	86%	81%	90%	92%	82%	68%	58%	65%	90%	92%	82%
Mali	4%	0%	17%	37%	13%	73%	10%	0%	34%	2%	0%	10%	0%	0%	0%
Mexico	38%	17%	58%	71%	75%	58%	86%	70%	94%	15%	6%	27%	68%	46%	82%
Mongolia	-	-	-	97%	94%	99%	-	-	-	-	-	-	-	-	-
Mozambique	1%	0%	3%	4%	0%	11%	2%	0%	8%	0%	0%	0%	0%	0%	0%
Myanmar (Burma)	4%	0%	11%	49%	26%	72%	14%	1%	34%	3%	0%	11%	4%	0%	12%
Nicaragua	8%	0%	29%	75%	39%	95%	40%	7%	79%	1%	0%	6%	10%	0%	31%
Niger	2%	0%	9%	10%	0%	41%	4%	0%	18%	1%	0%	4%	0%	0%	0%
Nigeria	8%	1%	19%	48%	11%	76%	24%	2%	49%	3%	0%	9%	2%	0%	8%
Norway	88%	85%	93%	97%	96%	98%	96%	96%	97%	-	-	-	94%	93%	96%
Paraguay	25%	2%	57%	87%	71%	93%	80%	59%	90%	25%	2%	60%	66%	40%	77%
Peru	12%	2%	29%	81%	52%	93%	53%	15%	80%	-	-	-	30%	3%	61%
Philippines	7%	0%	27%	77%	45%	95%	41%	6%	81%	12%	0%	40%	36%	4%	72%
Russia	41%	33%	45%	98%	98%	98%	64%	55%	70%	9%	7%	11%	79%	70%	82%
Rwanda	1%	0%	5%	10%	0%	37%	2%	0%	8%	-	-	-	0%	0%	0%
Senegal	5%	0%	20%	58%	17%	85%	32%	4%	65%	2%	0%	11%	0%	0%	2%
Serbia	91%	87%	95%	38%	13%	60%	76%	80%	70%	19%	8%	31%	45%	29%	62%
South Africa	27%	3%	75%	79%	70%	91%	69%	54%	90%	-	-	-	34%	12%	69%
Suriname	38%	29%	44%	66%	66%	58%	80%	67%	84%	31%	10%	54%	83%	69%	88%
Switzerland	77%	79%	80%	92%	92%	91%	64%	73%	54%	-	-	-	59%	60%	58%
Taiwan	61%	42%	70%	99%	98%	99%	-	-	-	95%	88%	98%	99%	98%	99%
Thailand	14%	1%	39%	97%	93%	97%	90%	82%	90%	18%	1%	45%	63%	39%	72%
Togo	3%	0%	10%	36%	3%	70%	6%	0%	21%	1%	0%	3%	0%	0%	1%
Turkey	39%	17%	65%	41%	23%	64%	99%	97%	100%	21%	13%	36%	96%	91%	98%
Uganda	3%	0%	11%	17%	0%	52%	5%	0%	19%	-	-	-	-	-	-
United Kingdom	75%	53%	87%	97%	97%	97%	98%	98%	98%	-	-	-	98%	97%	99%
Uruguay	46%	26%	67%	97%	96%	97%	99%	97%	99%	42%	20%	60%	85%	74%	90%
Vietnam	1%	0%	4%	91%	76%	96%	49%	11%	82%	9%	0%	29%	23%	1%	56%

Note:
This table shows the share of households possessing different assets for all households (first and fifth expenditure quintile, respectively) in different countries.

Table C.7: Average carbon footprint and average carbon intensity per expenditure quintile

	Average carbon footprint [tCO_2]						Average carbon intensity [$kgCO_2$/USD]					
		Expenditure quintile						Expenditure quintile				
Country	All	EQ1	EQ2	EQ3	EQ4	EQ5	All	EQ1	EQ2	EQ3	EQ4	EQ5
Argentina	17.3	9.2	13.5	16.4	21.3	26.1	1.28	1.69	1.40	1.26	1.13	0.90
Armenia	4.6	2.4	3.6	4.4	5.1	7.6	1.22	1.38	1.34	1.33	1.20	0.84
Australia	42.0	27.5	35.5	42.2	49.1	55.9	0.76	0.99	0.83	0.74	0.69	0.53
Austria	19.9	15.9	18.4	19.3	21.6	24.4	0.60	0.74	0.65	0.58	0.56	0.44
Bangladesh	0.8	0.3	0.5	0.6	0.9	1.6	0.32	0.34	0.31	0.31	0.33	0.34
Barbados	14.7	6.1	10.8	16.2	18.7	21.8	0.86	0.83	0.87	0.94	0.90	0.75
Belgium	22.1	18.5	21.9	22.2	22.6	25.5	0.75	0.85	0.80	0.79	0.71	0.60
Benin	1.2	0.4	0.7	1.0	1.2	2.9	0.40	0.37	0.38	0.37	0.36	0.51
Bolivia	1.7	0.8	1.4	1.8	2.1	2.4	0.43	0.45	0.44	0.44	0.44	0.40
Brazil	8.1	2.5	4.3	6.4	9.5	17.7	0.84	1.05	0.85	0.82	0.78	0.69
Bulgaria	4.5	2.6	3.2	4.3	5.5	6.7	0.81	0.76	0.77	0.85	0.86	0.80
Burkina Faso	1.3	0.3	0.6	0.8	1.4	3.5	0.40	0.31	0.35	0.36	0.41	0.55
Cambodia	2.8	1.3	1.9	2.4	3.2	5.0	0.50	0.52	0.55	0.50	0.48	0.47
Canada	32.0	21.6	27.3	34.0	37.7	39.4	0.67	0.77	0.68	0.67	0.65	0.58
Chile	11.7	5.7	8.5	10.9	13.7	19.5	0.69	0.84	0.74	0.70	0.63	0.51
Colombia	3.3	1.1	1.9	2.6	3.7	7.3	0.57	0.68	0.64	0.59	0.52	0.43
Costa Rica	5.1	1.9	3.4	4.4	6.4	9.5	0.43	0.38	0.45	0.44	0.46	0.41
Côte d'Ivoire	1.0	0.4	0.7	0.9	1.1	2.1	0.27	0.23	0.26	0.26	0.25	0.33
Croatia	10.0	5.7	8.7	9.7	11.6	14.2	0.78	0.64	0.81	0.79	0.82	0.83
Cyprus	18.5	12.6	17.6	18.5	21.0	22.6	0.75	0.82	0.82	0.74	0.71	0.66
Czechia	18.3	15.9	17.5	18.1	18.0	22.0	1.72	1.85	1.76	1.81	1.65	1.54
Denmark	18.2	17.4	17.9	16.1	18.1	21.5	0.50	0.58	0.52	0.48	0.47	0.43
Dominican Republic	4.6	1.9	2.9	3.8	4.7	9.8	0.54	0.47	0.49	0.52	0.52	0.69
Ecuador	2.3	1.0	1.4	1.8	2.5	4.8	0.36	0.44	0.34	0.32	0.33	0.35
Egypt	1.5	1.1	1.3	1.5	1.7	2.0	0.62	0.61	0.60	0.61	0.63	0.66
El Salvador	2.6	1.0	1.8	2.3	2.9	5.2	0.51	0.71	0.59	0.48	0.41	0.39
Estonia	8.8	4.9	6.9	8.8	9.8	13.9	0.80	0.90	0.89	0.82	0.75	0.67
Ethiopia	0.1	0.0	0.1	0.1	0.1	0.2	0.10	0.13	0.11	0.09	0.09	0.08
Finland	17.5	13.3	15.4	18.3	18.3	22.2	0.56	0.57	0.57	0.61	0.55	0.49
France	16.5	11.9	15.7	17.8	17.8	19.5	0.65	0.72	0.69	0.68	0.62	0.53
Georgia	2.7	1.2	2.2	2.7	3.3	4.1	1.04	0.99	1.05	1.07	1.08	1.00
Germany	34.0	29.8	31.1	32.9	34.9	41.3	1.21	1.40	1.26	1.22	1.16	1.03
Ghana	0.6	0.2	0.3	0.5	0.8	1.3	0.20	0.13	0.16	0.18	0.24	0.29
Greece	13.8	9.3	11.7	13.6	14.9	19.6	0.77	0.85	0.82	0.79	0.73	0.64
Guatemala	3.0	0.4	1.1	2.1	3.6	7.7	0.40	0.15	0.24	0.40	0.53	0.69
Guinea-Bissau	0.9	0.3	0.4	0.7	0.9	2.4	0.20	0.16	0.16	0.18	0.20	0.29
Hungary	9.8	5.9	8.6	10.1	11.5	13.1	1.16	1.06	1.18	1.23	1.20	1.11
India	1.8	0.8	1.1	1.4	2.1	3.4	1.07	1.03	1.06	1.08	1.10	1.06
Indonesia	2.9	1.1	1.9	2.6	3.6	5.5	1.05	1.05	1.05	1.05	1.07	1.06
Iraq	9.6	5.3	7.6	9.2	11.0	15.0	0.80	0.98	0.87	0.82	0.73	0.60
Ireland	28.8	21.1	27.1	29.6	33.4	32.7	0.95	1.11	1.05	0.94	0.91	0.74
Israel	22.4	14.7	20.2	23.0	26.1	28.0	0.62	0.78	0.67	0.60	0.58	0.47
Italy	19.1	12.8	17.2	19.1	21.9	24.7	0.85	0.99	0.91	0.83	0.80	0.71
Jordan	14.1	6.8	10.2	13.2	17.1	23.1	1.13	0.95	1.05	1.16	1.22	1.26
Kenya	1.2	0.2	0.5	0.8	1.3	3.0	0.42	0.38	0.37	0.40	0.43	0.51

Table C.7: Average carbon footprint and average carbon intensity per expenditure quintile *(continued)*

Country	All	EQ1	EQ2	EQ3	EQ4	EQ5	All	EQ1	EQ2	EQ3	EQ4	EQ5
Latvia	6.8	3.5	4.7	5.8	8.0	12.1	0.68	0.78	0.67	0.64	0.67	0.62
Liberia	0.7	0.1	0.3	0.6	0.9	1.5	0.20	0.11	0.16	0.22	0.24	0.29
Lithuania	4.8	2.6	3.3	4.0	6.2	8.0	0.47	0.43	0.42	0.46	0.53	0.52
Luxembourg	23.6	21.3	22.1	23.4	25.3	26.1	0.54	0.71	0.59	0.50	0.48	0.41
Malawi	0.1	0.0	0.0	0.0	0.0	0.2	0.03	0.01	0.02	0.02	0.03	0.08
Maldives	4.8	3.1	4.4	5.0	5.6	6.1	0.26	0.31	0.28	0.26	0.23	0.21
Mali	1.4	0.5	0.8	1.1	1.8	3.0	0.36	0.33	0.37	0.34	0.37	0.41
Mexico	6.6	2.4	4.3	5.9	8.0	12.8	1.10	0.98	1.08	1.14	1.17	1.13
Mongolia	5.6	4.3	5.5	5.8	6.1	6.4	1.17	1.49	1.38	1.21	1.06	0.73
Morocco	4.5	2.6	3.3	3.9	4.9	8.1	0.62	0.68	0.62	0.60	0.58	0.60
Mozambique	1.3	0.0	0.1	0.4	0.9	5.0	0.25	0.24	0.15	0.19	0.23	0.44
Myanmar (Burma)	1.3	0.4	0.7	0.9	1.4	2.9	0.46	0.37	0.41	0.42	0.47	0.64
Netherlands	27.4	27.0	27.7	25.5	26.0	30.9	0.84	0.98	0.89	0.82	0.77	0.71
Nicaragua	1.7	0.1	0.5	0.9	1.8	4.9	0.26	0.11	0.17	0.25	0.33	0.44
Niger	0.4	0.0	0.1	0.1	0.3	1.3	0.10	0.05	0.07	0.08	0.10	0.22
Nigeria	1.5	0.4	0.9	1.4	2.0	2.7	0.44	0.28	0.36	0.45	0.51	0.58
Norway	30.4	22.9	29.1	30.8	32.9	36.5	0.65	0.80	0.72	0.65	0.58	0.48
Pakistan	2.2	0.9	1.4	1.8	2.6	4.4	0.57	0.38	0.47	0.56	0.65	0.76
Paraguay	4.2	1.5	3.2	4.1	4.9	7.6	0.59	0.57	0.68	0.60	0.55	0.54
Peru	2.8	1.3	2.3	2.8	3.2	4.2	0.72	0.90	0.83	0.72	0.62	0.52
Philippines	2.2	0.6	1.1	1.8	2.8	4.9	0.44	0.30	0.38	0.46	0.51	0.55
Poland	18.5	11.5	16.0	18.0	20.6	26.5	1.60	1.56	1.74	1.75	1.66	1.28
Portugal	16.6	11.1	14.3	16.4	18.7	22.4	1.00	1.23	1.07	1.00	0.91	0.77
Romania	4.2	2.0	3.3	4.3	5.0	6.5	0.80	0.59	0.76	0.85	0.89	0.89
Russia	10.3	5.1	7.7	8.9	11.0	18.9	1.29	1.37	1.33	1.23	1.25	1.29
Rwanda	0.1	0.0	0.0	0.0	0.1	0.6	0.04	0.02	0.02	0.02	0.03	0.11
Senegal	2.0	0.5	1.0	1.8	2.5	4.3	0.25	0.14	0.17	0.25	0.29	0.38
Serbia	8.0	4.1	6.9	8.1	9.5	11.5	0.97	0.83	0.97	0.99	1.00	1.07
Slovakia	12.6	10.6	11.7	13.1	12.8	15.0	1.06	1.22	1.10	1.15	1.00	0.84
South Africa	14.3	3.4	5.6	8.2	14.4	39.9	2.04	2.04	1.98	2.03	2.08	2.07
Spain	16.5	9.2	14.1	17.0	19.9	22.2	0.74	0.78	0.78	0.76	0.72	0.65
Suriname	1.6	0.7	1.1	1.6	2.1	2.6	0.23	0.25	0.24	0.23	0.23	0.18
Sweden	14.3	12.1	13.8	14.9	13.7	17.0	0.48	0.55	0.51	0.50	0.43	0.43
Switzerland	22.1	19.4	21.2	22.1	22.9	25.0	0.29	0.32	0.30	0.30	0.28	0.25
Taiwan	23.9	15.5	20.9	24.0	27.4	31.9	1.17	1.17	1.17	1.18	1.18	1.16
Thailand	6.3	1.6	3.2	5.4	8.1	13.2	1.58	1.42	1.64	1.71	1.61	1.50
Togo	0.9	0.2	0.4	0.6	1.1	2.0	0.26	0.16	0.23	0.23	0.28	0.42
Turkey	16.2	9.2	13.3	15.9	18.0	24.6	1.75	1.81	1.98	1.85	1.68	1.44
Uganda	0.3	0.1	0.1	0.1	0.2	0.9	0.20	0.29	0.17	0.15	0.15	0.26
United Kingdom	25.6	14.2	22.0	27.3	29.6	34.7	0.83	0.95	0.92	0.87	0.77	0.62
United States	39.9	28.3	36.8	39.8	43.3	51.5	0.99	1.16	1.12	0.99	0.92	0.77
Uruguay	5.6	2.6	3.9	5.1	6.7	9.6	0.28	0.33	0.29	0.28	0.26	0.24
Vietnam	1.2	0.4	0.8	1.1	1.5	2.1	0.53	0.57	0.55	0.53	0.51	0.47

Note:

This table shows average carbon footprints in tCO_2 and average carbon intensity in $kgCO_2$/USD for households in all countries of our sample. We estimate household-weighted averages for the whole population and per expenditure quintile.

Table C.8: Hyperparameters for boosted regression tree models

	Selected hyperparameters			Model performance		
Country	`max_depth`	η	`mtry`	MAE	RMSE	R^2
Argentina	13	0.0029	10	0.50	0.73	0.27
Armenia	12	0.0012	12	0.60	0.97	0.27
Australia	3	0.0183	8	0.25	0.34	0.22
Austria	3	0.0080	11	0.26	0.36	0.21
Bangladesh	6	0.0082	8	0.08	0.13	0.17
Barbados	8	0.0018	11	0.40	0.60	0.23
Belgium	4	0.0052	4	0.27	0.37	0.13
Benin	7	0.0099	14	0.22	0.34	0.34
Bolivia	3	0.0285	14	0.12	0.17	0.41
Brazil	12	0.0016	11	0.38	0.60	0.19
Bulgaria	13	0.0013	4	0.37	0.83	0.01
Burkina Faso	7	0.0047	14	0.19	0.32	0.47
Cambodia	5	0.0050	6	0.22	0.33	0.21
Canada	7	0.0019	7	0.24	0.35	0.16
Chile	8	0.0014	3	0.24	0.34	0.12
Colombia	6	0.0094	11	0.27	0.43	0.20
Costa Rica	5	0.0064	12	0.27	0.41	0.25
Côte d'Ivoire	8	0.0122	13	0.17	0.29	0.43
Croatia	8	0.0010	5	0.42	0.60	0.07
Cyprus	6	0.0021	5	0.31	0.42	0.08
Czechia	3	0.0017	3	0.54	0.89	0.10
Denmark	4	0.0025	3	0.31	0.44	0.05
Dominican Republic	7	0.0087	8	0.22	0.35	0.42
Ecuador	6	0.0065	12	0.12	0.27	0.42
Egypt	12	0.0019	11	0.11	0.15	0.27
El Salvador	9	0.0045	12	0.26	0.45	0.31
Estonia	8	0.0016	4	0.36	0.48	0.03
Ethiopia	10	0.0075	14	0.03	0.07	0.19
Finland	7	0.0018	5	0.29	0.38	0.08
France	13	0.0011	4	0.39	0.54	0.08
Georgia	12	0.0028	11	0.51	0.76	0.32
Germany	11	0.0023	4	0.41	0.57	0.10
Ghana	5	0.0080	10	0.12	0.24	0.36
Greece	8	0.0013	4	0.28	0.37	0.07
Guatemala	8	0.0039	12	0.20	0.33	0.46
Guinea-Bissau	7	0.0065	9	0.14	0.25	0.18
Hungary	11	0.0014	5	0.51	0.68	0.03
India	11	0.0132	16	0.19	0.29	0.41
Indonesia	12	0.0029	13	0.28	0.39	0.37
Iraq	11	0.0017	13	0.28	0.42	0.27
Ireland	7	0.0018	4	0.40	0.61	0.14
Israel	10	0.0016	14	0.27	0.37	0.23
Italy	8	0.0054	3	0.31	0.40	0.10
Jordan	12	0.0032	12	0.30	0.41	0.59
Kenya	11	0.0062	6	0.21	0.35	0.15
Latvia	5	0.0015	3	0.46	0.60	0.13
Liberia	8	0.0066	11	0.15	0.25	0.12
Lithuania	5	0.0059	4	0.36	0.52	0.07
Luxembourg	7	0.0025	4	0.22	0.29	0.17
Malawi	4	0.0118	13	0.03	0.12	0.20
Maldives	4	0.0076	8	0.10	0.14	0.16

Table C.8: Hyperparameters for boosted regression tree models *(continued)*

Country	max_depth	η	mtry	MAE	RMSE	R^2
Mali	6	0.0119	11	0.20	0.30	0.41
Mexico	13	0.0023	16	0.42	0.62	0.31
Mongolia	10	0.0015	5	0.70	0.99	0.20
Morocco	6	0.0010	6	0.16	0.24	0.07
Mozambique	6	0.0100	13	0.27	0.50	0.19
Myanmar (Burma)	3	0.0082	10	0.25	0.38	0.18
Netherlands	8	0.0022	3	0.23	0.31	0.16
Nicaragua	5	0.0100	10	0.13	0.25	0.50
Niger	5	0.0061	11	0.07	0.17	0.52
Nigeria	7	0.0103	11	0.18	0.26	0.35
Norway	4	0.0066	11	0.33	0.48	0.23
Pakistan	7	0.0062	5	0.22	0.29	0.25
Paraguay	4	0.0088	11	0.29	0.47	0.24
Peru	7	0.0074	15	0.24	0.43	0.53
Philippines	6	0.0125	10	0.12	0.17	0.45
Poland	11	0.0012	6	0.85	2.01	0.04
Portugal	3	0.0182	5	0.34	0.44	0.18
Romania	10	0.0010	5	0.39	0.65	0.07
Russia	7	0.0021	10	0.41	0.71	0.27
Rwanda	3	0.0133	8	0.03	0.11	0.50
Senegal	6	0.0047	15	0.11	0.20	0.35
Serbia	3	0.0015	10	0.46	1.19	0.05
Slovakia	9	0.0010	4	0.61	0.99	0.13
South Africa	10	0.0028	11	0.47	0.69	0.36
Spain	7	0.0011	5	0.32	0.46	0.09
Suriname	3	0.0077	10	0.16	0.28	0.03
Sweden	3	0.0064	3	0.31	0.41	0.06
Switzerland	3	0.0077	7	0.17	0.28	0.15
Taiwan	11	0.0037	6	0.20	0.25	0.36
Thailand	8	0.0053	12	0.42	0.56	0.33
Togo	6	0.0080	10	0.18	0.37	0.44
Turkey	8	0.0021	10	0.76	1.15	0.22
Uganda	4	0.0081	9	0.15	0.33	0.29
United Kingdom	6	0.0016	9	0.37	0.55	0.16
United States	3	0.0223	5	0.33	0.45	0.13
Uruguay	4	0.0057	11	0.13	0.21	0.34
Vietnam	10	0.0111	9	0.10	0.13	0.27

Note:
This table shows hyperparameters selected for fitting boosted regression tree models after hyperparameter tuning. `max_depth` is the maximum depth of trees; η is the learning rate; `mtry` is the number of features included in each tree. MAE is the mean absolute error of predictions; RMSE is the root mean squared error of predictions; R^2 is the squared correlation of prediction errors and a measure for goodness of fit. Unit of MAE and RMSE is $kgCO_2$ per USD. We show MAE, RMSE and R^2 for fivefold cross-validation on the entire dataset. Note that we repeat fivefold cross-validation with selected hyperparameters, e.g., in Table C.10.

Table C.9: Comparing median carbon intensity and horizontal heterogeneity between first and fifth expenditure quintile

Country	$\overline{e}_r^1$	$\overline{e}_r^5$	$\overline{H}_r^1$	$\overline{H}_r^5$	$\overline{H}_r^{1*}$	$\overline{H}_r^{5*}$	$\widehat{V}_r^1$	$\widehat{H}_r^1$	$\widehat{H}_r^{1*}$
Argentina	1.44	0.74	3.15	1.78	1.45	0.88	1.93	1.77	1.64
Armenia	1.07	0.58	3.64	2.30	1.56	0.88	1.85	1.59	1.78
Australia	0.91	0.50	1.41	0.80	0.64	0.35	1.83	1.75	1.80
Austria	0.62	0.39	1.66	0.85	0.87	0.42	1.58	1.95	2.09
Bangladesh	0.32	0.31	0.33	0.46	0.15	0.20	1.03	0.71	0.75
Barbados	0.58	0.63	2.17	1.52	1.05	0.78	0.91	1.43	1.35
Belgium	0.80	0.56	1.52	0.94	0.72	0.47	1.42	1.62	1.53
Benin	0.18	0.38	1.26	1.42	0.71	0.61	0.49	0.88	1.17
Bolivia	0.39	0.37	0.80	0.56	0.33	0.28	1.05	1.44	1.17
Brazil	0.85	0.59	2.12	1.33	0.84	0.68	1.45	1.59	1.23
Bulgaria	0.60	0.66	1.43	1.11	0.50	0.49	0.92	1.29	1.04
Burkina Faso	0.02	0.46	1.58	1.41	0.65	0.52	0.04	1.12	1.25
Cambodia	0.45	0.39	1.25	0.96	0.63	0.46	1.13	1.30	1.36
Canada	0.66	0.56	1.73	0.77	0.79	0.36	1.19	2.24	2.22
Chile	0.76	0.48	1.23	0.63	0.57	0.31	1.58	1.96	1.83
Colombia	0.46	0.32	1.87	0.88	0.86	0.42	1.44	2.11	2.06
Costa Rica	0.24	0.29	1.22	1.18	0.54	0.65	0.83	1.03	0.83
Côte d'Ivoire	0.06	0.20	1.06	1.09	0.32	0.38	0.30	0.97	0.84
Croatia	0.52	0.74	1.56	1.93	0.83	0.83	0.70	0.81	1.00
Cyprus	0.79	0.61	1.68	1.04	0.89	0.54	1.29	1.61	1.66
Czechia	1.56	1.41	2.83	2.14	1.12	0.90	1.11	1.32	1.26
Denmark	0.39	0.34	1.58	1.09	0.68	0.40	1.13	1.45	1.69
Dominican Republic	0.36	0.49	1.14	1.74	0.45	0.91	0.75	0.65	0.49
Ecuador	0.34	0.27	1.02	0.78	0.37	0.37	1.26	1.31	1.00
Egypt	0.59	0.61	0.46	0.73	0.21	0.30	0.98	0.63	0.71
El Salvador	0.18	0.24	2.11	1.24	1.24	0.50	0.75	1.70	2.49
Estonia	0.78	0.59	1.89	1.22	0.86	0.63	1.31	1.56	1.36
Ethiopia	0.07	0.08	0.34	0.11	0.11	0.04	0.98	3.11	2.66
Finland	0.45	0.40	1.25	0.96	0.63	0.52	1.12	1.30	1.23
France	0.50	0.43	1.79	1.19	0.95	0.66	1.15	1.51	1.44
Georgia	0.69	0.78	2.75	2.42	1.20	1.34	0.88	1.14	0.89
Germany	1.29	0.93	2.18	1.49	1.02	0.69	1.38	1.46	1.48
Ghana	0.07	0.16	0.49	1.10	0.11	0.23	0.42	0.45	0.49
Greece	0.77	0.59	1.32	0.92	0.69	0.46	1.30	1.44	1.50
Guatemala	0.06	0.50	0.54	1.72	0.13	0.83	0.13	0.32	0.16
Guinea-Bissau	0.05	0.18	0.68	0.96	0.16	0.29	0.29	0.70	0.55
Hungary	0.86	1.03	2.23	1.96	1.14	1.01	0.84	1.14	1.13
India	0.98	0.99	0.81	1.11	0.40	0.50	0.99	0.73	0.80
Indonesia	0.96	0.99	1.71	1.44	0.86	0.72	0.97	1.18	1.20
Iraq	0.87	0.53	1.51	1.01	0.68	0.48	1.65	1.50	1.41
Ireland	0.96	0.67	2.34	1.18	1.06	0.59	1.44	1.98	1.80
Israel	0.65	0.38	1.52	0.93	0.69	0.46	1.72	1.62	1.49
Italy	0.94	0.66	1.56	0.99	0.81	0.49	1.42	1.57	1.66
Jordan	0.76	1.27	1.75	2.02	0.84	1.28	0.60	0.87	0.66
Kenya	0.29	0.42	0.96	1.05	0.43	0.47	0.69	0.91	0.91
Latvia	0.47	0.47	2.10	1.50	1.13	0.91	0.98	1.40	1.24

Table C.9: Comparing median carbon intensity and horizontal heterogeneity between first and fifth expenditure quintile *(continued)*

Liberia	0.06	0.18	0.38	0.94	0.08	0.28	0.34	0.41	0.29
Lithuania	0.24	0.45	1.42	1.39	0.69	0.70	0.54	1.02	0.98
Luxembourg	0.61	0.37	1.33	0.76	0.66	0.40	1.65	1.75	1.67
Malawi	0.01	0.02	0.02	0.32	0.01	0.04	0.37	0.07	0.15
Maldives	0.29	0.18	0.50	0.36	0.22	0.17	1.57	1.42	1.24
Mali	0.02	0.35	1.39	1.06	0.73	0.60	0.05	1.31	1.21
Mexico	0.73	1.03	2.05	1.95	0.94	1.00	0.72	1.05	0.93
Mongolia	1.20	0.52	3.84	1.98	2.29	0.93	2.30	1.94	2.46
Morocco	0.63	0.53	0.75	0.81	0.32	0.39	1.19	0.93	0.82
Mozambique	0.03	0.15	1.30	2.01	0.21	0.55	0.20	0.65	0.38
Myanmar (Burma)	0.25	0.46	0.90	1.78	0.39	0.72	0.54	0.51	0.55
Netherlands	0.93	0.65	1.18	0.89	0.59	0.45	1.42	1.32	1.32
Nicaragua	0.03	0.26	0.46	1.33	0.14	0.47	0.11	0.34	0.29
Niger	0.03	0.09	0.10	0.82	0.03	0.34	0.35	0.12	0.09
Nigeria	0.18	0.54	0.82	0.94	0.39	0.43	0.34	0.87	0.90
Norway	0.62	0.40	2.00	1.07	1.14	0.55	1.54	1.87	2.05
Pakistan	0.29	0.70	0.83	1.05	0.40	0.54	0.41	0.79	0.75
Paraguay	0.37	0.45	1.96	1.14	0.88	0.53	0.82	1.71	1.65
Peru	0.70	0.47	2.51	0.84	1.31	0.39	1.50	2.97	3.34
Philippines	0.26	0.52	0.50	0.71	0.20	0.33	0.50	0.71	0.61
Poland	1.27	0.90	2.55	2.42	0.96	0.64	1.42	1.05	1.51
Portugal	1.15	0.72	1.78	1.09	0.91	0.57	1.60	1.63	1.60
Romania	0.49	0.75	1.37	1.75	0.61	0.86	0.66	0.78	0.71
Russia	1.08	1.13	2.60	1.88	1.01	0.97	0.96	1.38	1.04
Rwanda	0.00	0.02	0.04	0.68	0.00	0.04	0.17	0.06	0.10
Senegal	0.07	0.28	0.51	0.98	0.15	0.28	0.27	0.53	0.53
Serbia	0.73	0.78	1.26	2.29	0.55	0.54	0.94	0.55	1.03
Slovakia	0.83	0.67	3.06	1.74	1.54	0.79	1.24	1.76	1.95
South Africa	1.86	1.99	2.49	2.38	1.09	1.11	0.93	1.05	0.98
Spain	0.62	0.59	1.57	1.04	0.76	0.55	1.05	1.50	1.38
Suriname	0.18	0.12	0.83	0.54	0.31	0.16	1.53	1.54	1.94
Sweden	0.45	0.38	1.65	0.98	0.91	0.58	1.19	1.69	1.56
Switzerland	0.23	0.19	0.89	0.62	0.38	0.23	1.23	1.42	1.62
Taiwan	1.13	1.16	0.93	1.12	0.47	0.63	0.98	0.84	0.74
Thailand	1.45	1.51	2.23	2.10	1.20	1.28	0.96	1.06	0.93
Togo	0.00	0.14	1.17	1.64	0.03	0.74	0.02	0.71	0.04
Turkey	1.33	1.25	4.52	2.36	2.18	0.95	1.06	1.91	2.29
Uganda	0.04	0.09	1.17	1.12	0.40	0.28	0.41	1.05	1.45
United Kingdom	0.81	0.54	2.27	1.11	1.28	0.54	1.51	2.05	2.35
United States	1.12	0.73	1.94	1.02	0.96	0.46	1.54	1.89	2.07
Uruguay	0.24	0.20	0.88	0.56	0.35	0.29	1.21	1.57	1.24

Vietnam	0.56	0.46	0.50	0.41	0.23	0.21	1.20	1.23	1.12

Note:

This table shows the median carbon intensity in the first expenditure quintile ($\bar{e}_r^1$) and in the fifth quintile ($\bar{e}_r^5$). It displays the difference between the 5$^{\text{th}}$ (20$^{\text{th}}$) and 95$^{\text{th}}$ (80$^{\text{th}}$) within-quintile percentile for the first ($\overline{H}_r^1$ and $\overline{H}_r^{1*}$) and the fifth quintile ($\overline{H}_r^5$ and $\overline{H}_r^{5*}$). It also compares the median carbon intensity in the first income quintile to that in the fifth quintile ($\widehat{V}_r^1$). Lastly, it displays our comparison index that enables the comparison of within-quintile variation between the first and fifth quintile ($\widehat{H}_r^1$ and $\widehat{H}_r^{1*}$, respectively).

Table C.10: Evaluation of boosted regression tree models

		Sparse model			Rich model		
Country	Mean	MAE	RMSE	R^2	MAE	RMSE	R^2
Argentina	1.28	0.57	0.82	0.14	0.50	0.73	0.27
Armenia	1.22	0.70	1.09	0.04	0.60	0.97	0.26
Australia	0.76	0.26	0.35	0.17	0.25	0.34	0.21
Austria	0.60	0.29	0.40	0.07	0.26	0.37	0.21
Bangladesh	0.32	0.09	0.14	0.02	0.08	0.13	0.16
Barbados	0.86	0.48	0.68	0.02	0.40	0.60	0.24
Belgium	0.75	0.28	0.37	0.09	0.27	0.36	0.13
Benin	0.40	0.30	0.42	0.04	0.22	0.34	0.35
Bolivia	0.43	0.16	0.22	0.03	0.12	0.17	0.41
Brazil	0.84	0.42	0.65	0.05	0.38	0.60	0.19
Bulgaria	0.81	0.37	0.82	0.01	0.37	0.83	0.01
Burkina Faso	0.40	0.30	0.42	0.05	0.19	0.31	0.48
Cambodia	0.50	0.26	0.37	0.01	0.22	0.33	0.22
Canada	0.67	0.27	0.38	0.02	0.24	0.35	0.16
Chile	0.69	0.24	0.36	0.06	0.24	0.35	0.12
Colombia	0.57	0.31	0.48	0.02	0.27	0.43	0.20
Costa Rica	0.43	0.35	0.47	0.02	0.27	0.41	0.26
Côte d'Ivoire	0.27	0.26	0.38	0.01	0.17	0.29	0.43
Croatia	0.78	0.42	0.61	0.06	0.42	0.61	0.06
Cyprus	0.75	0.32	0.43	0.05	0.31	0.42	0.08
Czechia	1.72	0.57	0.94	0.01	0.54	0.89	0.11
Denmark	0.50	0.33	0.46	0.00	0.31	0.44	0.05
Dominican Republic	0.54	0.32	0.45	0.04	0.22	0.35	0.42
Ecuador	0.36	0.19	0.36	0.03	0.12	0.26	0.46
Egypt	0.62	0.12	0.18	0.03	0.11	0.15	0.27
El Salvador	0.51	0.37	0.54	0.02	0.26	0.45	0.31
Estonia	0.80	0.37	0.49	0.01	0.36	0.48	0.03
Ethiopia	0.10	0.04	0.08	0.01	0.03	0.07	0.19
Finland	0.56	0.30	0.39	0.01	0.28	0.38	0.08
France	0.65	0.41	0.56	0.02	0.39	0.54	0.08
Georgia	1.04	0.66	0.93	0.02	0.51	0.76	0.32
Germany	1.21	0.43	0.61	0.02	0.41	0.57	0.10
Ghana	0.20	0.16	0.30	0.04	0.12	0.24	0.36
Greece	0.77	0.29	0.39	0.02	0.27	0.37	0.08
Guatemala	0.40	0.28	0.42	0.13	0.19	0.32	0.48
Guinea-Bissau	0.20	0.16	0.27	0.06	0.14	0.25	0.19
Hungary	1.16	0.52	0.67	0.00	0.51	0.68	0.03
India	1.07	0.25	0.38	0.01	0.19	0.29	0.41
Indonesia	1.05	0.36	0.49	0.02	0.28	0.39	0.37
Iraq	0.80	0.29	0.44	0.20	0.28	0.42	0.29
Ireland	0.95	0.42	0.65	0.06	0.40	0.61	0.14
Israel	0.62	0.30	0.42	0.03	0.27	0.37	0.23
Italy	0.85	0.32	0.42	0.03	0.31	0.40	0.10
Jordan	1.13	0.50	0.64	0.03	0.30	0.41	0.59
Kenya	0.42	0.24	0.39	0.02	0.21	0.36	0.15
Latvia	0.68	0.49	0.63	0.03	0.46	0.60	0.13
Liberia	0.20	0.15	0.26	0.09	0.15	0.25	0.13
Lithuania	0.47	0.37	0.53	0.05	0.36	0.52	0.07
Luxembourg	0.54	0.22	0.30	0.13	0.22	0.29	0.16
Malawi	0.03	0.04	0.13	0.04	0.03	0.12	0.20
Maldives	0.26	0.11	0.15	0.01	0.10	0.14	0.15

Table C.10: Evaluation of boosted regression tree models *(continued)*

Country	Mean	MAE	RMSE	R^2	MAE	RMSE	R^2
Mali	0.36	0.30	0.39	0.02	0.20	0.30	0.41
Mexico	1.10	0.54	0.76	0.01	0.42	0.62	0.31
Mongolia	1.17	0.77	1.09	0.05	0.70	0.99	0.19
Morocco	0.62	0.17	0.25	0.01	0.16	0.24	0.07
Mozambique	0.25	0.28	0.51	0.14	0.27	0.50	0.18
Myanmar (Burma)	0.46	0.27	0.41	0.05	0.25	0.38	0.17
Netherlands	0.84	0.25	0.33	0.09	0.23	0.31	0.16
Nicaragua	0.26	0.23	0.36	0.03	0.12	0.25	0.51
Niger	0.10	0.11	0.23	0.17	0.07	0.17	0.52
Nigeria	0.44	0.23	0.31	0.05	0.18	0.26	0.35
Norway	0.65	0.37	0.53	0.04	0.33	0.47	0.23
Pakistan	0.57	0.24	0.32	0.09	0.22	0.29	0.25
Paraguay	0.59	0.35	0.55	0.00	0.29	0.48	0.23
Peru	0.72	0.37	0.60	0.08	0.24	0.43	0.53
Philippines	0.44	0.15	0.20	0.16	0.12	0.17	0.45
Poland	1.60	0.81	2.04	0.01	0.84	2.00	0.04
Portugal	1.00	0.37	0.48	0.04	0.34	0.45	0.17
Romania	0.80	0.42	0.67	0.00	0.39	0.65	0.07
Russia	1.29	0.51	0.83	0.01	0.41	0.71	0.28
Rwanda	0.04	0.05	0.14	0.17	0.03	0.11	0.48
Senegal	0.25	0.15	0.24	0.05	0.11	0.20	0.34
Serbia	0.97	0.46	1.23	0.00	0.47	1.19	0.05
Slovakia	1.06	0.66	1.04	0.02	0.61	0.99	0.14
South Africa	2.04	0.58	0.86	0.02	0.47	0.69	0.36
Spain	0.74	0.34	0.48	0.00	0.32	0.46	0.09
Suriname	0.23	0.17	0.28	0.02	0.16	0.28	0.03
Sweden	0.48	0.32	0.43	0.01	0.31	0.41	0.06
Switzerland	0.29	0.20	0.32	0.00	0.17	0.28	0.14
Taiwan	1.17	0.25	0.31	0.01	0.20	0.25	0.36
Thailand	1.58	0.51	0.66	0.08	0.42	0.56	0.33
Togo	0.26	0.31	0.48	0.04	0.18	0.37	0.43
Turkey	1.75	0.88	1.30	0.02	0.76	1.15	0.22
Uganda	0.20	0.20	0.38	0.04	0.15	0.33	0.29
United Kingdom	0.83	0.40	0.58	0.05	0.37	0.55	0.16
United States	0.99	0.34	0.47	0.07	0.33	0.45	0.13
Uruguay	0.28	0.18	0.27	0.00	0.13	0.21	0.35
Vietnam	0.53	0.11	0.15	0.08	0.10	0.13	0.28

Note:
This table shows performance metrics for boosted regression tree models including exclusively household expenditures ('Sparse model') and including all available features ('Rich model'). MAE is the mean absolute error of predictions; RMSE is the root mean squared error of predictions; R^2 is the squared correlation of prediction errors. Unit of MAE and RMSE is $kgCO_2$ per USD. We show MAE, RMSE and R^2 for fivefold cross-validation on the entire dataset.

Table C.11: Feature importance across countries by cluster

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
A	Greece	0.55	1.30	0.02	0.03	0.03							
A	Morocco	0.54	1.19	0.02	0.01	0.04							
A	Finland	0.54	1.12	0.01	0.03	0.03							
A	France	0.53	1.15	0.01	0.02	0.04							
A	Sweden	0.53	1.19	0.02	0.01	0.03							
A	Denmark	0.53	1.13	0.01	0.03	0.01							
A	Cyprus	0.52	1.29	0.03	0.03	0.01							
A	Poland	0.52	1.42	0.01	0.01	0.02							
A	Italy	0.52	1.42	0.03	0.05	0.03							
A	Belgium	0.52	1.42	0.05	0.03	0.05							
A	Germany	0.52	1.38	0.02	0.05	0.03							
A	Spain	0.50	1.05	0.01	0.03	0.05							
A	Estonia	0.49	1.31	0.01	0.01	0.00							
A	Ireland	0.49	1.44	0.06	0.04	0.05							
A	Czechia	0.49	1.11	0.02	0.02	0.06							
A	Suriname	0.49	1.53	0.00	0.01	0.01		0.00		0.00	0.00		0.00
A	Hungary	0.48	0.84	0.01	0.02	0.01							
A	United States	0.48	1.54	0.05	0.05	0.03							
A	Serbia	0.47	0.94	0.02	0.01	0.01	0.00		0.00		0.00		0.01
A	Romania	0.47	0.66	0.01	0.02	0.04							
A	Croatia	0.47	0.70	0.03	0.02	0.01							
A	Slovakia	0.46	1.24	0.03	0.05	0.06							
A	Latvia	0.45	0.98	0.02	0.04	0.07							
A	Netherlands	0.45	1.42	0.07	0.04	0.05							
A	Canada	0.44	1.19	0.04	0.03	0.06					0.02		0.01
A	Bulgaria	0.44	0.92	0.00	0.00	0.00							
A	Lithuania	0.44	0.54	0.03	0.03	0.01							
A	Brazil	0.41	1.45	0.04	0.03	0.04	0.00	0.00	0.01		0.05	0.02	0.01
A	Maldives	0.41	1.57	0.02	0.02	0.07		0.00			0.00	0.02	0.02
A	Colombia	0.41	1.44	0.05	0.04	0.03	0.00	0.03			0.03	0.03	0.01
A	Cambodia	0.39	1.13	0.04	0.03	0.05		0.03		0.00	0.01	0.05	
A	Liberia	0.37	0.34	0.05	0.03	0.03	0.00	0.01		0.00	0.00	0.01	0.00
A	Chile	0.37	1.58	0.05	0.07	0.00							
A	Austria	0.36	1.58	0.07	0.03	0.04			0.01		0.05	0.00	0.00
A	Luxembourg	0.34	1.65	0.09	0.05	0.02							
A	Kenya	0.34	0.69	0.02	0.03	0.05	0.00	0.02		0.03			
A	Myanmar (Burma)	0.34	0.54	0.03	0.02	0.02	0.00	0.01		0.01	0.02	0.04	0.02
A	Mozambique	0.29	0.20	0.06	0.03	0.05	0.00	0.02		0.01	0.00	0.01	0.00
A	Norway	0.29	1.54	0.07	0.03	0.09					0.03	0.01	0.00
A	Israel	0.28	1.72	0.06	0.06	0.05					0.06	0.00	0.01
A	Switzerland	0.28	1.23	0.02	0.01	0.03					0.03	0.01	0.04
A	Mongolia	0.28	2.30	0.06	0.02	0.11							0.00

Table C.11: Feature importance across countries by cluster *(continued)*

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
A	Australia	0.27	1.83	0.10	0.07	0.04							
A	Guinea-Bissau	0.27	0.29	0.03	0.04	0.04	0.00	0.00		0.01	0.02	0.05	0.01
A	Argentina	0.25	1.93	0.08	0.04	0.07	0.00	0.01	0.01		0.05	0.01	0.01
A	Portugal	0.24	1.60	0.05	0.10	0.03							
A	Malawi	0.24	0.37	0.04	0.04	0.01	0.00	0.01		0.00	0.04	0.04	0.01
A	Bangladesh	0.19	1.03	0.03	0.03	0.03	0.02				0.00	0.02	0.03
A	Ethiopia	0.17	0.98	0.03	0.03	0.07	0.00	0.02		0.04	0.00	0.00	0.00
A	United Kingdom	0.17	1.51	0.06	0.01	0.02			0.03		0.03		0.00
B	Jordan	0.15	0.60	0.04	0.06	0.15		0.00			0.32		0.01
B	Mexico	0.14	0.72	0.03	0.03	0.05	0.00	0.02			0.11	0.01	0.06
B	Dominican Republic	0.14	0.75	0.03	0.05	0.07	0.00	0.02		0.00	0.12	0.11	0.03
B	Guatemala	0.11	0.13	0.03	0.07	0.04	0.00	0.08		0.00	0.15	0.07	0.03
B	Philippines	0.06	0.50	0.03	0.04	0.08	0.01				0.03	0.08	0.18
B	South Africa	0.06	0.93	0.08	0.03	0.04	0.01	0.01	0.01	0.01	0.15	0.00	0.03
B	Taiwan	0.05	0.98	0.06	0.11	0.00					0.18	0.01	0.00
B	Georgia	0.04	0.88	0.03	0.04	0.06		0.06			0.12	0.00	0.02
B	Russia	0.03	0.96	0.02	0.04	0.06					0.14	0.00	0.02
B	Thailand	0.03	0.96	0.03	0.08	0.03	0.00	0.03			0.05	0.07	0.05
B	Indonesia	0.01	0.97	0.06	0.03	0.05	0.01	0.05		0.00	0.03	0.09	0.06
B	Uruguay	-0.05	1.21	0.06	0.03	0.04	0.00	0.00	0.02	0.00	0.14	0.05	0.01
B	Egypt	-0.06	0.98	0.05	0.05	0.04	0.00	0.00		0.00	0.09		0.03
B	Vietnam	-0.08	1.20	0.09	0.03	0.07	0.01			0.00	0.00	0.01	0.08
B	Barbados	-0.13	0.91	0.04	0.04	0.02	0.00	0.02		0.00	0.10		0.02
B	Costa Rica	-0.14	0.83	0.03	0.02	0.03	0.00	0.03		0.00	0.12	0.03	0.00
C	Togo	0.33	0.02	0.04	0.09	0.03	0.01	0.02		0.01	0.02	0.21	0.01
C	Burkina Faso	0.29	0.04	0.06	0.05	0.06	0.01	0.01		0.01	0.04	0.23	0.01
C	Mali	0.28	0.05	0.03	0.04	0.08	0.01	0.01		0.02	0.02	0.19	0.01
C	Nigeria	0.27	0.34	0.01	0.05	0.07	0.04	0.06			0.02	0.07	0.03
C	Niger	0.27	0.35	0.04	0.04	0.03	0.02	0.02		0.02	0.10	0.22	0.02
C	Côte d'Ivoire	0.26	0.30	0.03	0.11	0.08	0.01	0.02		0.01	0.01	0.16	0.01
C	Senegal	0.21	0.27	0.02	0.03	0.03	0.04	0.05		0.01	0.04	0.07	0.05
C	Benin	0.21	0.49	0.03	0.09	0.03	0.01	0.01		0.02	0.03	0.12	0.01
C	Ghana	0.13	0.42	0.02	0.05	0.07	0.01	0.05		0.01	0.04	0.08	0.03
C	India	0.08	0.99	0.03	0.04	0.14	0.01	0.06		0.00	0.02	0.08	0.03
C	Pakistan	-0.09	0.41	0.06	0.07	0.10	0.01						
D	Peru	0.28	1.50	0.18	0.04	0.05	0.00	0.19		0.00	0.02	0.02	0.03
D	Ecuador	0.19	1.26	0.14	0.03	0.03	0.00	0.06		0.00	0.13	0.05	0.02
D	Nicaragua	0.11	0.11	0.05	0.04	0.03	0.01	0.15		0.00	0.12	0.10	0.01
D	Bolivia	0.08	1.05	0.10	0.04	0.06	0.01	0.06			0.05	0.04	0.04
D	El Salvador	-0.04	0.75	0.08	0.06	0.02	0.00	0.06		0.00	0.05	0.01	0.01
D	Iraq	-0.08	1.65	0.14	0.03	0.01	0.00	0.00	0.01	0.00	0.07	0.00	0.02

Table C.11: Feature importance across countries by cluster *(continued)*

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
D	Paraguay	-0.15	0.82	0.03	0.02	0.01	0.00	0.10			0.03	0.03	0.01
E	Uganda	0.59	0.41	0.04	0.03	0.04	0.01	0.02		0.10	0.02	0.04	0.00
E	Rwanda	0.58	0.17	0.06	0.03	0.07		0.05		0.09	0.09	0.06	0.02
F	Turkey	0.61	1.06	0.02	0.02	0.01		0.03	0.09		0.03	0.00	0.02
F	Armenia	0.55	1.85	0.06	0.02	0.05	0.00		0.08		0.05	0.00	0.01

Note:

This table shows feature importance in percent (based on absolute average SHAP values per feature) across all countries and per cluster. We adjust feature importance for model accuracy. Column 'Vertical distribution' shows average values.

Table C.12: Feature importance across countries by cluster - non-adjusted

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
A	Poland	0.52	1.42	0.27	0.31	0.42							
A	Greece	0.52	1.30	0.25	0.41	0.34							
A	Italy	0.51	1.42	0.29	0.44	0.28							
A	United States	0.50	1.54	0.35	0.39	0.25							
A	Germany	0.50	1.38	0.24	0.46	0.30							
A	Ireland	0.49	1.44	0.39	0.26	0.35							
A	Slovakia	0.49	1.24	0.21	0.33	0.46							
A	Netherlands	0.48	1.42	0.42	0.26	0.32							
A	Belgium	0.47	1.42	0.39	0.22	0.39							
A	Finland	0.47	1.12	0.18	0.43	0.39							
A	Morocco	0.46	1.19	0.32	0.20	0.49							
A	Denmark	0.46	1.13	0.21	0.51	0.28							
A	Latvia	0.45	0.98	0.19	0.29	0.52							
A	Hungary	0.45	0.84	0.21	0.47	0.32							
A	Cyprus	0.43	1.29	0.42	0.45	0.13							
A	Australia	0.42	1.83	0.46	0.33	0.21							
A	Sweden	0.42	1.19	0.26	0.16	0.57							
A	Portugal	0.41	1.60	0.27	0.56	0.17							
A	Estonia	0.41	1.31	0.44	0.46	0.10							
A	Czechia	0.41	1.11	0.20	0.20	0.60							
A	France	0.40	1.15	0.12	0.29	0.59							
A	Romania	0.38	0.66	0.16	0.28	0.57							
A	Lithuania	0.38	0.54	0.35	0.47	0.18							
A	Bulgaria	0.37	0.92	0.35	0.55	0.10							
A	Spain	0.36	1.05	0.07	0.30	0.62							
A	Luxembourg	0.35	1.65	0.56	0.34	0.10							
A	Chile	0.34	1.58	0.41	0.57	0.02							
A	Mongolia	0.33	2.30	0.33	0.11	0.55							0.01
A	Croatia	0.33	0.70	0.53	0.34	0.12							
A	Norway	0.30	1.54	0.29	0.12	0.40					0.14	0.03	0.01
A	Suriname	0.29	1.53	0.11	0.42	0.30		0.02		0.01	0.04		0.10
A	Pakistan	0.26	0.41	0.26	0.30	0.39	0.05						
A	Canada	0.25	1.19	0.23	0.16	0.39					0.15		0.06
A	Israel	0.15	1.72	0.27	0.25	0.20					0.25	0.00	0.03
A	Maldives	0.14	1.57	0.16	0.12	0.44		0.01			0.02	0.11	0.14
A	Serbia	0.14	0.94	0.38	0.11	0.29	0.00		0.06		0.00		0.16
A	Mozambique	0.13	0.20	0.33	0.20	0.26	0.01	0.09		0.06	0.01	0.04	0.01
A	Argentina	0.12	1.93	0.28	0.14	0.26	0.00	0.02	0.03		0.20	0.02	0.06
A	Liberia	0.12	0.34	0.35	0.21	0.22	0.04	0.05		0.03	0.01	0.07	0.02
A	Austria	0.10	1.58	0.36	0.14	0.18			0.06		0.24	0.01	0.02
B	Barbados	0.36	0.91	0.17	0.16	0.08	0.00	0.09		0.00	0.44		0.07
B	Georgia	0.36	0.88	0.09	0.12	0.17		0.18			0.37	0.00	0.07

Table C.12: Feature importance across countries by cluster - non-adjusted *(continued)*

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
B	Costa Rica	0.35	0.83	0.10	0.10	0.12	0.00	0.14		0.00	0.45	0.10	0.00
B	Mexico	0.31	0.72	0.09	0.11	0.17	0.00	0.06			0.37	0.03	0.18
B	Ecuador	0.29	1.26	0.31	0.06	0.07	0.00	0.13		0.00	0.29	0.11	0.03
B	Uruguay	0.28	1.21	0.18	0.09	0.11	0.00	0.01	0.05	0.00	0.41	0.13	0.02
B	Russia	0.27	0.96	0.06	0.15	0.23					0.48	0.00	0.08
B	South Africa	0.27	0.93	0.23	0.09	0.12	0.04	0.02	0.02	0.02	0.40	0.00	0.07
B	Jordan	0.25	0.60	0.07	0.10	0.26		0.00			0.55		0.02
B	Egypt	0.22	0.98	0.18	0.19	0.16	0.00	0.00		0.00	0.35		0.11
B	Taiwan	0.20	0.98	0.16	0.31	0.00					0.49	0.03	0.01
B	El Salvador	0.19	0.75	0.28	0.21	0.07	0.01	0.19		0.01	0.16	0.03	0.04
B	Paraguay	0.18	0.82	0.14	0.08	0.06	0.00	0.42			0.14	0.13	0.03
B	Bolivia	0.18	1.05	0.25	0.11	0.14	0.04	0.16			0.12	0.09	0.10
B	Switzerland	0.17	1.23	0.13	0.07	0.23					0.23	0.04	0.31
B	Guatemala	0.17	0.13	0.07	0.14	0.08	0.01	0.16		0.01	0.31	0.15	0.07
B	Peru	0.14	1.50	0.34	0.07	0.09	0.00	0.36		0.01	0.04	0.04	0.06
B	Thailand	0.13	0.96	0.08	0.23	0.09	0.00	0.09			0.15	0.21	0.15
B	Dominican Republic	0.12	0.75	0.07	0.11	0.16	0.00	0.05		0.00	0.29	0.26	0.07
B	Colombia	0.12	1.44	0.23	0.18	0.14	0.00	0.13			0.13	0.14	0.04
B	Nicaragua	0.09	0.11	0.10	0.07	0.06	0.01	0.29		0.01	0.23	0.20	0.03
B	Cambodia	0.09	1.13	0.17	0.15	0.21		0.16		0.02	0.05	0.24	
B	Indonesia	0.04	0.97	0.16	0.08	0.13	0.01	0.12		0.01	0.07	0.23	0.17
B	Brazil	0.03	1.45	0.20	0.16	0.20	0.01	0.01	0.05		0.24	0.10	0.03
B	Malawi	-0.01	0.37	0.19	0.21	0.04	0.01	0.05		0.02	0.21	0.22	0.04
B	Vietnam	-0.02	1.20	0.33	0.11	0.23	0.02			0.00	0.00	0.04	0.27
B	Iraq	-0.03	1.65	0.48	0.11	0.04	0.01	0.01	0.02	0.00	0.25	0.00	0.06
C	Togo	0.36	0.02	0.08	0.21	0.07	0.03	0.04		0.02	0.04	0.48	0.02
C	Mali	0.36	0.05	0.08	0.09	0.19	0.03	0.01		0.06	0.06	0.46	0.03
C	Burkina Faso	0.31	0.04	0.13	0.11	0.13	0.02	0.02		0.02	0.07	0.48	0.02
C	Benin	0.31	0.49	0.08	0.25	0.10	0.03	0.03		0.05	0.09	0.35	0.02
C	Niger	0.30	0.35	0.09	0.08	0.06	0.04	0.03		0.03	0.20	0.42	0.04
C	Côte d'Ivoire	0.29	0.30	0.06	0.24	0.19	0.01	0.04		0.02	0.03	0.36	0.03
C	Nigeria	0.25	0.34	0.04	0.14	0.20	0.10	0.16			0.06	0.20	0.09
C	Senegal	0.24	0.27	0.05	0.09	0.10	0.11	0.15		0.02	0.13	0.22	0.13
C	Bangladesh	0.16	1.03	0.19	0.21	0.17	0.13				0.01	0.12	0.17
C	Ghana	0.14	0.42	0.06	0.15	0.19	0.03	0.15		0.02	0.10	0.22	0.08
C	Guinea-Bissau	0.14	0.29	0.13	0.23	0.19	0.01	0.02		0.03	0.08	0.25	0.05
C	Myanmar (Burma)	0.04	0.54	0.19	0.13	0.13	0.02	0.03		0.05	0.13	0.22	0.09
C	India	0.01	0.99	0.08	0.09	0.35	0.03	0.14		0.01	0.05	0.19	0.06
C	Philippines	-0.01	0.50	0.07	0.08	0.18	0.02				0.07	0.18	0.40
D	Ethiopia	0.51	0.98	0.14	0.15	0.36	0.01	0.08		0.23	0.00	0.00	0.02
D	Uganda	0.49	0.41	0.15	0.09	0.12	0.03	0.05		0.33	0.07	0.13	0.02
D	Kenya	0.43	0.69	0.11	0.19	0.33	0.03	0.15		0.18			

Table C.12: Feature importance across countries by cluster - non-adjusted *(continued)*

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
D	Rwanda	0.34	0.17	0.13	0.07	0.15		0.10		0.19	0.18	0.13	0.05
E	Armenia	0.56	1.85	0.22	0.06	0.17	0.00		0.30		0.20	0.00	0.04
E	Turkey	0.47	1.06	0.11	0.09	0.03		0.12	0.43		0.13	0.00	0.08
E	United Kingdom	0.31	1.51	0.35	0.08	0.14			0.21		0.20		0.01

Note:
This table shows feature importance in percent (based on absolute average SHAP values per feature) across all countries and per cluster. Feature importance is unadjusted for model accuracy. Column 'Vertical distribution' shows average values.

Table C.13: Feature importance across countries by cluster - imputed

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
A	Hungary	0.47	0.84	0.01	0.02	0.01	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Denmark	0.46	1.13	0.01	0.03	0.01	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Romania	0.46	0.66	0.01	0.02	0.04	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	France	0.45	1.15	0.01	0.02	0.04	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Sweden	0.45	1.19	0.02	0.01	0.03	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Morocco	0.44	1.19	0.02	0.01	0.04	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Finland	0.43	1.12	0.01	0.03	0.03	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Bulgaria	0.43	0.92	0.00	0.00	0.00	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Spain	0.43	1.05	0.01	0.03	0.05	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Croatia	0.42	0.70	0.03	0.02	0.01	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Poland	0.42	1.42	0.01	0.01	0.02	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Estonia	0.41	1.31	0.01	0.01	0.00	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Lithuania	0.41	0.54	0.03	0.03	0.01	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Greece	0.40	1.30	0.02	0.03	0.03	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Myanmar (Burma)	0.40	0.54	0.03	0.02	0.02	0.00	0.01	0.03	0.01	0.02	0.04	0.02
A	Czechia	0.37	1.11	0.02	0.02	0.06	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Kenya	0.37	0.69	0.02	0.03	0.05	0.00	0.02	0.03	0.03	0.06	0.05	0.02
A	Switzerland	0.33	1.23	0.02	0.01	0.03	0.01	0.03	0.03	0.01	0.03	0.01	0.04
A	Cyprus	0.33	1.29	0.03	0.03	0.01	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Guinea-Bissau	0.32	0.29	0.03	0.04	0.04	0.00	0.00	0.03	0.01	0.02	0.05	0.01
A	Malawi	0.32	0.37	0.04	0.04	0.01	0.00	0.01	0.03	0.00	0.04	0.04	0.01
A	Suriname	0.31	1.53	0.00	0.01	0.01	0.01	0.00	0.03	0.00	0.00	0.05	0.00
A	Latvia	0.30	0.98	0.02	0.04	0.07	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Liberia	0.29	0.34	0.05	0.03	0.03	0.00	0.01	0.03	0.00	0.00	0.01	0.00
A	Cambodia	0.28	1.13	0.04	0.03	0.05	0.01	0.03	0.03	0.00	0.01	0.05	0.02
A	Canada	0.28	1.19	0.04	0.03	0.06	0.01	0.03	0.03	0.01	0.02	0.05	0.01
A	Germany	0.27	1.38	0.02	0.05	0.03	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Serbia	0.27	0.94	0.02	0.01	0.01	0.00	0.03	0.00	0.01	0.00	0.05	0.01
A	Italy	0.22	1.42	0.03	0.05	0.03	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Paraguay	0.22	0.82	0.03	0.02	0.01	0.00	0.10	0.03	0.01	0.03	0.03	0.01
A	Mozambique	0.21	0.20	0.06	0.03	0.05	0.00	0.02	0.03	0.01	0.00	0.01	0.00
A	Maldives	0.21	1.57	0.02	0.02	0.07	0.01	0.00	0.03	0.01	0.00	0.02	0.02
A	Barbados	0.20	0.91	0.04	0.04	0.02	0.00	0.02	0.03	0.00	0.10	0.05	0.02
A	Slovakia	0.19	1.24	0.03	0.05	0.06	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	United Kingdom	0.19	1.51	0.06	0.01	0.02	0.01	0.03	0.03	0.01	0.03	0.05	0.00
A	Ethiopia	0.18	0.98	0.03	0.03	0.07	0.00	0.02	0.03	0.04	0.00	0.00	0.00
A	Colombia	0.17	1.44	0.05	0.04	0.03	0.00	0.03	0.03	0.01	0.03	0.03	0.01
A	Costa Rica	0.17	0.83	0.03	0.02	0.03	0.00	0.03	0.03	0.00	0.12	0.03	0.00
A	Belgium	0.14	1.42	0.05	0.03	0.05	0.01	0.03	0.03	0.01	0.06	0.05	0.02
A	Brazil	0.13	1.45	0.04	0.03	0.04	0.00	0.00	0.01	0.01	0.05	0.02	0.01
A	Thailand	0.10	0.96	0.03	0.08	0.03	0.00	0.03	0.03	0.01	0.05	0.07	0.05
A	Indonesia	0.10	0.97	0.06	0.03	0.05	0.01	0.05	0.03	0.00	0.03	0.09	0.06

Table C.13: Feature importance across countries by cluster - imputed *(continued)*

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
B	Australia	0.30	1.83	0.10	0.07	0.04	0.01	0.03	0.03	0.01	0.06	0.05	0.02
B	Luxembourg	0.21	1.65	0.09	0.05	0.02	0.01	0.03	0.03	0.01	0.06	0.05	0.02
B	Iraq	0.18	1.65	0.14	0.03	0.01	0.00	0.00	0.01	0.00	0.07	0.00	0.02
B	Israel	0.17	1.72	0.06	0.06	0.05	0.01	0.03	0.03	0.01	0.06	0.00	0.01
B	Ecuador	0.16	1.26	0.14	0.03	0.03	0.00	0.06	0.03	0.00	0.13	0.05	0.02
B	Argentina	0.14	1.93	0.08	0.04	0.07	0.00	0.01	0.01	0.01	0.05	0.01	0.01
B	Bolivia	0.13	1.05	0.10	0.04	0.06	0.01	0.06	0.03	0.01	0.05	0.04	0.04
B	Portugal	0.12	1.60	0.05	0.10	0.03	0.01	0.03	0.03	0.01	0.06	0.05	0.02
B	Mongolia	0.09	2.30	0.06	0.02	0.11	0.01	0.03	0.03	0.01	0.06	0.05	0.00
B	Netherlands	0.07	1.42	0.07	0.04	0.05	0.01	0.03	0.03	0.01	0.06	0.05	0.02
B	Austria	0.07	1.58	0.07	0.03	0.04	0.01	0.03	0.01	0.01	0.05	0.00	0.00
B	Norway	0.07	1.54	0.07	0.03	0.09	0.01	0.03	0.03	0.01	0.03	0.01	0.00
B	El Salvador	0.06	0.75	0.08	0.06	0.02	0.00	0.06	0.03	0.00	0.05	0.01	0.01
B	Vietnam	0.04	1.20	0.09	0.03	0.07	0.01	0.03	0.03	0.00	0.00	0.01	0.08
B	Chile	0.01	1.58	0.05	0.07	0.00	0.01	0.03	0.03	0.01	0.06	0.05	0.02
B	United States	-0.06	1.54	0.05	0.05	0.03	0.01	0.03	0.03	0.01	0.06	0.05	0.02
B	Ireland	-0.07	1.44	0.06	0.04	0.05	0.01	0.03	0.03	0.01	0.06	0.05	0.02
C	Jordan	0.20	0.60	0.04	0.06	0.15	0.01	0.00	0.03	0.01	0.32	0.05	0.01
C	Guatemala	0.08	0.13	0.03	0.07	0.04	0.00	0.08	0.03	0.00	0.15	0.07	0.03
C	Taiwan	0.07	0.98	0.06	0.11	0.04	0.01	0.03	0.03	0.01	0.18	0.01	0.00
C	Russia	0.00	0.96	0.02	0.04	0.06	0.01	0.03	0.03	0.01	0.14	0.00	0.02
C	Dominican Republic	-0.01	0.75	0.03	0.05	0.07	0.00	0.02	0.03	0.00	0.12	0.11	0.03
C	South Africa	-0.03	0.93	0.08	0.03	0.04	0.01	0.01	0.01	0.01	0.15	0.00	0.03
C	Uruguay	-0.03	1.21	0.06	0.03	0.04	0.00	0.00	0.02	0.00	0.14	0.05	0.01
C	Mexico	-0.07	0.72	0.03	0.03	0.05	0.00	0.02	0.03	0.01	0.11	0.01	0.06
C	Georgia	-0.12	0.88	0.03	0.04	0.06	0.01	0.06	0.03	0.01	0.12	0.00	0.02
C	Egypt	-0.12	0.98	0.05	0.05	0.04	0.00	0.00	0.03	0.00	0.09	0.05	0.03
D	Nigeria	0.33	0.34	0.01	0.05	0.07	0.04	0.06	0.03	0.01	0.02	0.07	0.03
D	Senegal	0.29	0.27	0.02	0.03	0.03	0.04	0.05	0.03	0.01	0.04	0.07	0.05
D	India	0.09	0.99	0.03	0.04	0.14	0.01	0.06	0.03	0.00	0.02	0.08	0.03
D	Pakistan	0.01	0.41	0.06	0.07	0.10	0.01	0.03	0.03	0.01	0.06	0.05	0.02
D	Ghana	-0.03	0.42	0.02	0.05	0.07	0.01	0.05	0.03	0.01	0.04	0.08	0.03
D	Bangladesh	-0.14	1.03	0.03	0.03	0.03	0.02	0.03	0.03	0.01	0.00	0.02	0.03
E	Togo	0.47	0.02	0.04	0.09	0.03	0.01	0.02	0.03	0.01	0.02	0.21	0.01
E	Burkina Faso	0.45	0.04	0.06	0.05	0.06	0.01	0.01	0.03	0.01	0.04	0.23	0.01
E	Côte d'Ivoire	0.33	0.30	0.03	0.11	0.08	0.01	0.02	0.03	0.01	0.01	0.16	0.01
E	Mali	0.33	0.05	0.03	0.04	0.08	0.01	0.01	0.03	0.02	0.02	0.19	0.01
E	Benin	0.26	0.49	0.03	0.09	0.03	0.01	0.01	0.03	0.02	0.03	0.12	0.01
E	Niger	0.23	0.35	0.04	0.04	0.03	0.02	0.02	0.03	0.02	0.10	0.22	0.02
F	Turkey	0.55	1.06	0.02	0.02	0.01	0.01	0.03	0.09	0.01	0.03	0.00	0.02

Table C.13: Feature importance across countries by cluster - imputed *(continued)*

Cluster	Country	Silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
F	Armenia	0.47	1.85	0.06	0.02	0.05	0.00	0.03	0.08	0.01	0.05	0.00	0.01
G	Uganda	0.59	0.41	0.04	0.03	0.04	0.01	0.02	0.03	0.10	0.02	0.04	0.00
G	Rwanda	0.58	0.17	0.06	0.03	0.07	0.01	0.05	0.03	0.09	0.09	0.06	0.02
H	Peru	0.15	1.50	0.18	0.04	0.05	0.00	0.19	0.03	0.00	0.02	0.02	0.03
H	Nicaragua	-0.06	0.11	0.05	0.04	0.03	0.01	0.15	0.03	0.00	0.12	0.10	0.01
I	Philippines	0.00	0.50	0.03	0.04	0.08	0.01	0.03	0.03	0.01	0.03	0.08	0.18

Note:
This table shows feature importance in percent (based on absolute average SHAP values per feature) across all countries and per cluster. We adjust feature importance for model accuracy and impute missing information for feature importance based on average values per feature. Column 'Vertical distribution' shows average values.

Table C.14: Electricity generation in 88 countries (2021)

Country	TWh	Share of electricity production by source in percent (2021)								
		Hydro	Wind	Solar	Bioenergy	Renewables	Nuclear	Oil	Gas	Coal
Argentina	147	14%	9%	1%	1%	-	7%	5%	61%	2%
Armenia	7.3	30%	-	1%	-	-	25%	-	43%	-
Australia	247	6%	11%	11%	1%	-	-	2%	18%	51%
Austria	67	58%	10%	4%	7%	-	-	5%	16%	0%
Bangladesh	81	1%	0%	1%	0%	-	-	17%	68%	13%
Barbados	1.1	-	-	7%	-	-	-	93%	-	-
Belgium	99	0%	12%	6%	5%	-	51%	3%	23%	0%
Benin	0.2	-	-	4%	-	-	-	96%	-	-
Bolivia	11	31%	1%	4%	5%	-	-	-	58%	-
Brazil	663	55%	11%	3%	9%	-	2%	3%	14%	4%
Bulgaria	47	10%	3%	3%	5%	-	35%	1%	6%	36%
Burkina Faso	1.8	6%	-	7%	-	-	-	87%	-	-
Cambodia	8.7	46%	-	4%	3%	-	-	5%	-	42%
Canada	626	60%	6%	1%	1%	-	14%	0%	12%	6%
Chile	82	20%	9%	13%	-	0%	-	6%	18%	34%
Colombia	81	72%	0%	0%	1%	-	-	5%	15%	6%
Costa Rica	13	73%	12%	0%	0%	13%	-	1%	-	-
Cote d'Ivoire	11	30%	-	0%	-	-	-	20%	50%	-
Croatia	15	47%	14%	1%	7%	1%	-	0%	21%	10%
Cyprus	5.1	-	5%	9%	1%	-	-	85%	-	-
Czechia	84	3%	1%	3%	6%	-	37%	1%	9%	41%
Denmark	33	0%	49%	4%	26%	-	-	3%	5%	13%
Dominican Rep.	18	6%	7%	3%	1%	-	-	20%	36%	26%
Ecuador	32	79%	0%	0%	4%	-	-	13%	4%	-
Egypt	202	7%	2%	2%	-	-	-	13%	76%	-
El Salvador	6.6	30%	0%	17%	8%	24%	-	20%	-	-
Estonia	7.2	0%	10%	5%	25%	-	-	60%	1%	-
Ethiopia	15	95%	4%	0%	0%	-	-	0%	-	-
Finland	72	22%	11%	0%	19%	-	33%	5%	5%	4%
France	550	11%	7%	3%	2%	0%	69%	2%	6%	1%
Georgia	13	81%	1%	-	-	-	-	-	19%	-
Germany	582	3%	20%	8%	8%	0%	12%	4%	16%	28%

Table C.14: Electricity generation in 87 countries (2021) *(continued)*

Country	TWh	Hydro	Wind	Solar	Bioenergy	Renewables	Nuclear	Oil	Gas	Coal
Ghana	21	34%	-	0%	0%	-	-	17%	48%	-
Greece	55	11%	19%	10%	1%	-	-	9%	41%	10%
Guatemala	14	41%	2%	2%	20%	2%	-	14%	-	19%
Guinea-Bissau	0.1	-	-	-	-	-	-	100%	-	-
Hungary	36	1%	2%	11%	6%	0%	44%	1%	27%	8%
India	1714	9%	4%	4%	2%	-	3%	0%	4%	74%
Indonesia	309	8%	0%	0%	5%	5%	-	2%	18%	61%
Iraq	97	5%	-	0%	-	-	-	17%	78%	-
Ireland	32	2%	31%	0%	3%	-	-	7%	48%	9%
Israel	73	0%	0%	6%	0%	-	-	-	66%	27%
Italy	286	16%	7%	9%	7%	2%	-	4%	50%	5%
Jordan	22	0%	7%	16%	0%	-	-	8%	69%	-
Kenya	12	34%	13%	1%	1%	43%	-	8%	-	-
Latvia	5.8	46%	2%	0%	15%	-	-	-	36%	-
Liberia	0.9	58%	-	-	-	-	-	42%	-	-
Lithuania	4.2	9%	33%	5%	17%	-	-	8%	29%	-
Luxembourg	1.2	9%	25%	15%	32%	-	-	6%	14%	-
Malawi	1.4	70%	-	12%	1%	-	-	16%	-	-
Maldives	0.7	-	-	8%	-	-	-	92%	-	-
Mali	3.4	29%	-	1%	6%	-	-	64%	-	-
Mexico	337	10%	6%	4%	2%	1%	3%	10%	59%	4%
Mongolia	7.1	1%	7%	2%	-	-	-	-	-	90%
Morocco	41	3%	12%	4%	0%	-	-	11%	12%	58%
Mozambique	20	80%	-	0%	1%	-	-	6%	12%	-
Myanmar	22	40%	-	0%	1%	-	-	18%	36%	4%
Netherlands	122	0%	15%	9%	9%	-	3%	5%	47%	12%
Nicaragua	4.6	12%	14%	1%	11%	17%	-	45%	-	-
Niger	0.4	-	-	11%	-	-	-	89%	-	-
Nigeria	31	25%	-	0%	0%	-	-	0%	72%	2%
Norway	151	92%	7%	0%	0%	0%	-	0%	0%	0%
Pakistan	150	26%	2%	1%	1%	-	10%	11%	37%	12%
Paraguay	40	100%	-	-	0%	-	-	0%	-	-
Peru	58	55%	3%	1%	1%	-	-	7%	31%	1%

Table C.14: Electricity generation in 87 countries (2021) *(continued)*

Country	TWh	Hydro	Wind	Solar	Bioenergy	Renewables	Nuclear	Oil	Gas	Coal
Philippines	108	7%	1%	1%	2%	10%	-	18%	14%	45%
Poland	179	1%	9%	2%	5%	-	-	3%	9%	71%
Portugal	49	24%	27%	5%	8%	0%	-	3%	31%	2%
Romania	59	29%	11%	3%	1%	-	19%	2%	17%	18%
Russia	1110	19%	0%	0%	0%	0%	20%	1%	42%	17%
Rwanda	0.9	53%	-	7%	-	-	-	40%	-	-
Senegal	5.6	6%	4%	8%	2%	-	-	45%	32%	2%
Serbia	37	30%	3%	0%	1%	-	-	1%	1%	64%
Slovakia	30	15%	-	2%	6%	-	53%	4%	15%	6%
South Africa	223	1%	4%	3%	0%	-	5%	1%	-	86%
Spain	271	11%	23%	10%	3%	0%	21%	4%	26%	2%
Suriname	2	50%	-	1%	-	-	-	50%	-	-
Sweden	172	43%	16%	1%	8%	-	31%	2%	0%	0%
Switzerland	61	61%	0%	5%	0%	-	30%	4%	-	-
Taiwan	288	1%	1%	3%	1%	0%	10%	2%	38%	45%
Thailand	187	3%	2%	2%	7%	-	-	0%	65%	21%
Togo	0.6	24%	-	3%	-	-	-	73%	-	-
Turkey	331	17%	9%	4%	2%	3%	-	1%	33%	31%
Uganda	4.4	91%	-	3%	3%	-	-	3%	-	-
United Kingdom	307	2%	21%	4%	13%	0%	15%	3%	40%	2%
United States	4152	6%	9%	4%	1%	0%	19%	1%	38%	22%
Uruguay	16	33%	32%	3%	10%	-	-	2%	20%	-
Vietnam	245	31%	1%	11%	0%	-	-	0%	11%	47%

Note:
This table shows summary statistics for electricity generation in 88 different countries of our sample. It reports the share of electricity generated by each source in each country in 2021 [%] as well as the total annual electricity production [TWh]. Source: Ember (2023) retrieved through Our World in Data (Ritchie and Rosado 2020).

Table C.15: Average feature importance across country clusters

Cluster	Number	Average silhouette width	Vertical distribution	HH expenditures	Sociodemographic	Spatial	Electricity access	Cooking fuel	Heating fuel	Lighting fuel	Car own.	Motorcycle own.	Appliance own.
A	50	0.41	1.20	0.04	0.03	0.04	0.00	0.00	0.00	0.00	0.01	0.01	0.00
B	16	0.02	0.84	0.04	0.05	0.05	0.00	0.02	0.00	0.00	0.11	0.03	0.04
C	11	0.20	0.33	0.03	0.06	0.07	0.02	0.03	0.00	0.01	0.03	0.13	0.02
D	7	0.06	1.02	0.10	0.04	0.03	0.00	0.09	0.00	0.00	0.07	0.04	0.02
E	2	0.59	0.29	0.05	0.03	0.06	0.01	0.03	0.00	0.09	0.05	0.05	0.01
F	2	0.58	1.45	0.04	0.02	0.03	0.00	0.01	0.09	0.00	0.04	0.00	0.01

Note:
This table shows the average importance of features in percent (based on absolute average SHAP values per feature) across all countries from each Cluster A to F. We adjust feature importance for model accuracy. Column 'Vertical distribution' shows average values. Column 'number' refers to the number of countries assigned to this cluster.

Table C.16: Comparing vertical and horizontal distribution coefficients for different policies

Policy instrument	$\widehat{V}^1 > 1$	$\widehat{V}^1 < 1$	$\widehat{V}^1 \uparrow$	$\widehat{V}^1 \downarrow$	$\widehat{H}^1 > 1$	$\widehat{H}^1 < 1$	$\widehat{H}^1 \uparrow$	$\widehat{H}^1 \downarrow$
National climate policy	44	44			60	28		
International climate policy	47	41	44	44	57	31	30	58
Transport sector policy	29	59	10	78	50	38	28	60
Electricity sector policy	62	26	74	14	65	23	63	25

Note:

This table compares vertical and horizontal distribution coefficients for different policy instruments across all countries. Column '$\widehat{V}^1 > 1$' displays the number of countries in which poorer households consume more carbon-intensively compared to richer households, under consideration of each policy. Column '$\widehat{V}^1 < 1$' displays the number of countries in which richer households consume more carbon-intensively compared to poorer households, under consideration of each policy. Column '$\widehat{V}^1 \uparrow$' displays the number of countries in which $\widehat{V}^1$ increases in comparison to national climate policy, i.e., in which poorer households would consume more carbon-intensively compared to richer households and to the 'national climate policy'-scenario. Column '$\widehat{V}^1 \downarrow$' displays the number of countries in which $\widehat{V}^1$ decreases in comparison to national climate policy, i.e., in which poorer households would consume less carbon-intensively compared to richer households and to the 'national climate policy'-scenario. Column '$\widehat{H}^1 > 1$' displays the number of countries in which carbon intensity is more heterogeneous across poorer households compared to richer households, under consideration of each policy. Column '$\widehat{H}^1 < 1$' displays the number of countries in which carbon intensity is more heterogeneous across richer households compared to poorer households, under consideration of each policy. Column '$\widehat{H}^1 \uparrow$' displays the number of countries in which $\widehat{H}^1$ increases in comparison to national climate policy, i.e., in which heterogeneity across poorer households compared to richer households would increase in comparison to the 'national climate policy'-scenario. Column '$\widehat{H}^1 \downarrow$' displays the number of countries in which $\widehat{H}^1$ decreases in comparison to national climate policy, i.e., in which heterogeneity across poorer households compared to richer households would decrease in comparison to the 'national climate policy'-scenario.

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D Supplementary information

D.1 Data availability

Data from household budget surveys are available from statistical agencies subject to permission and possible allowances. See also Table C.1. Data from GTAP are available through GTAP, subject to academic subscription. Descriptive analyses for carbon pricing reforms and stylized compensation policies can be accessed and customized through a separate webtool.

D.2 Code availability

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.

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