Skatteforsk
Centre for Tax Research

Working Paper No. 8

Distributional Impacts of Heterogenous Carbon Prices in the EU

July 2024

Magnus Merkle
Norwegian University of Life Sciences

Geoffrey Dolphin
International Monetary Fund

1. Skatteforsk's Working Paper Series is financed through support from The Research Council of Norway (Grant number 341289). The views expressed in this Working Paper are those of the author(s) and do not necessarily represent the views of Skatteforsk - Centre for Tax Research.
2. The views expressed in this paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

Distributional Impacts of Heterogenous Carbon Prices in the EU

Magnus Merkle[a] and Geoffroy Dolphin[b]

[a] *Norwegian University of Life Sciences, School of Economics and Business, Chr. Magnus Falsens vei 18, 1430 Ås, Norway*

[b] *International Monetary Fund, European Department, 700 19th St NW, Washington, DC, 20431, United States*

Abstract[1]

We analyse the consequences of carbon price heterogeneity on households in The EU from 2010 to 2020. Accounting for both heterogeneity in carbon pricing across emission sources and the indirect effects from inter-industry linkages, we obtain two key findings. First, due to widespread carbon pricing exemptions, household burdens are lower than previously estimated. Second, lower-income groups are affected disproportionately, because they spend a smaller share of their expenditure on products that benefit from exemptions than their higher-income counterparts. Therefore, imposing uniform carbon prices both within and across countries would reduce carbon pricing regressivity on household expenditure in the EU. A global price would be most effective in this regard, as it would raise carbon prices embodied in EU imports. Further, because EU economies are open and apply higher average carbon prices than their trade partners, the domestic revenues exceed the costs embodied in EU household consumptions bundles. This increases the scope for reducing the burden of carbon pricing on lower-income households through revenue redistribution. Our results imply that the ongoing extension of carbon pricing to more sectors through the EU ETS II and the introduction of the EU's CBAM should make carbon pricing less regressive, all else equal.

Keywords

Carbon pricing, tax incidence, climate policy

JEL-codes

H22, H31, Q52, Q56, Q58

[1] The authors would like to thank Dallas Burtraw, Stephan Danninger, Romain Duval, Eirik Romstad, and Knut Einar Rosendahl for their helpful comments. The research has benefited from brown bag discussions at the IMF (European Department, August 2023) and the Norwegian University of Life Sciences (Climate Resources Energy and Environment Research Group, October 2023). The authors are also indebted to Mengyu Li and Manfred Lenzen for their guidance on the GLORIA dataset and for feedback on some methodological steps. The authors are grateful to Simon Feindt and Jeroen van den Bergh for discussing preliminary results.

1. Introduction

Achieving the goal of the Paris Agreement requires significant reductions in global greenhouse gas (GHG) emissions. Economists have long recommended pricing GHG emissions as an environmentally effective and economically efficient climate policy instrument (Tirole, 2012). Accordingly, several jurisdictions have introduced carbon pricing mechanisms, although rarely at a rate consistent with estimates of the social cost of carbon (Hsiang et al., 2017; Rennert et al., 2022; U.S. EPA, 2023) or with levels needed to achieve the goals of the Paris Agreement (CPLC, 2017; Rogelj et al., 2018).[2] Furthermore, carbon pricing mechanisms in place to date continue to elude more than three quarters of global GHG emissions (World Bank Group, 2023) and have come with sector or fuel exemptions and price rebates that have dampened the marginal and average price signals faced by emitters across sectors (Dolphin et al., 2020; Finch & van den Bergh, 2022).

One reason for carbon price heterogeneity across emission sources within jurisdictions is the—perceived or actual—heterogenous impact of uniform pricing on firms and households (Douenne & Fabre, 2022), which may trigger political resistance from the most affected and politically organized ones among them, forcing governments to accommodate lower prices on their emissions (Cullenward & Victor, 2020; Olson, 1965; Stigler, 1971; Tavoni & Winkler, 2021). The dynamics of perceived and actual incidence of carbon prices are particularly relevant within countries because, in democracies, they affect support for climate policy and ultimately determine their odds of implementation.

Incidence and distributional impacts of carbon pricing have been subject to much academic and policy interest (reviewed by Maestre-Andrés et al., 2019). Recent reviews suggest that carbon pricing mechanisms have a regressive impact when looking at expenditures in developed countries—low-income households tend to be hit harder than high-income ones (Boyce, 2018; Peñasco et al., 2021), unless when revenues are redistributed in a way that mitigates this impact.

Most investigations to date have not considered that the scope of implemented policies differs across sectors and/or fuels. In most cases, studies on the distributional impacts of carbon pricing have either only considered a single sector (e.g. Andersson & Atkinson, 2020), or assumed a uniform price across all sectors (e.g. Feindt et al., 2021; Fremstad & Paul, 2019; Goulder et al., 2019). Assuming a uniform price is particularly suited to forward looking simulations of ideal-world policy scenarios. Less empirical work has examined within-country price heterogeneity issues, even though these are recognized as a gap in the research on the socio-economic impacts of climate policy and environmental taxation (Timilsina, 2022). In an analytical study on heterogeneous carbon prices and distribution, Abrell et al. (2018) show that deviations from uniform carbon pricing can be justified to achieve optimal outcomes when we accept heterogenous preferences across household groups, or when social equity concerns at the outset lead us to weigh the utilities of different household groups differently. A more economically efficient alternative to non-uniform carbon pricing to alleviate regressive effects can be household-specific revenue transfers (e.g. Hänsel et al., 2022). Such mechanisms might, however, be difficult to implement in practice.

In this paper, we evaluate whether the observed non-uniform carbon pricing regimes in the EU have indeed made climate mitigation less regressive, and how more uniform policies compare in terms of distributional outcome. We aim to contribute to recent advances in microsimulation that account not only for direct taxation but also for indirect tax impacts (Akoğuz et al., 2020; Amores et al., 2022), in a setting where carbon pricing is applied with varying stringency, i.e., differing scope and price level.

[2] In 2023, there were 73 carbon pricing instruments in force in 39 national and 33 subnational jurisdictions (World Bank Group, 2023).

Europe is a particularly interesting case for an analysis of carbon pricing incidence, given its long history of environmental taxation, ongoing and planned climate policy initiatives, as well as the fact that carbon pricing policy developments have resulted in heterogenous cross-sector and cross-country carbon prices. Several European countries started carbon taxation in the early 1990s, and the EU Emissions Trading System (EU ETS), introduced in 2005, was the world's largest carbon market until the introduction of China's ETS in 2021. Over time, the EU ETS has been increasing in stringency. Considerable changes were implemented in the step from phase II to phase III in 2013, when more sectors were included, more gases were covered, and free allocation of permits ceased to be the default method of allocation (European Commission, 2023b). Prices fluctuated between zero and 42 EUR per ton of CO_2 equivalent until 2020, before increasing to over 100 EUR in 2023 and receding since then (Trading Economics, 2023). As a further strengthening of its carbon pricing regime, the EU introduced a carbon border adjustment mechanism (CBAM) intended to reduce carbon leakage by aligning carbon prices on emissions embodied in certain imports with domestic prices. Earlier research for the case of Europe suggests that pricing indirect emissions embodied in imports can make impacts more progressive (Feindt et al., 2021), given that richer households buy more imported products.

Our research is the first to be based on a comprehensive sectoral carbon price dataset (Dolphin & Merkle, forthcoming; Dolphin & Xiahou, 2022), matched with multi-regional input-output time series (Lenzen et al., 2017, 2021) and detailed household expenditure data from the EU. We first compute the household incidence of observed heterogenous carbon prices across The EU from 2010 to 2020 and identify distributional trends over time. We then decompose changes over time to identify whether distributional impacts have changed due to changes in policies, carbon intensities, economic interdependencies, or consumption bundles. Finally, we run simulations of various alternative carbon pricing scenarios in comparison to the observed heterogenous regimes in place. In particular, we quantify the immediate incidence and distributional impacts of a hypothetical uniformization of prices.

Our results suggest that on average, the uniformization of carbon prices within countries as well as across countries would have made policies less regressive in most EU countries. The least regressive expenditure impacts are obtained when imposing a uniform global carbon price. This is because pricing exemptions between 2010 and 2020 have benefited high-income households more than low-income households. These results suggest that ongoing efforts to broaden the scope of carbon pricing at the EU level—particularly the closing of domestic pricing gaps—and the adoption of border carbon price adjustments on imported products will improve the income distribution impact of carbon pricing—making it more progressive, all else equal. Given that all countries of the EU have comparably open economies, our model shows that lump-sum transfers of carbon pricing revenue can offset and exceed the burden on low-income households in the EU.

2. Literature Review

Carbon pricing has long been economists' preferred instrument to tackle harmful GHG emissions as, in theory, it yields the largest possible emissions reductions for any given price (Timilsina, 2022). Following an approach first suggested by Pigou (1920), the rationale is to internalize the environmental cost by altering relative prices of inputs to production and of final products, to incentivize shifts towards decarbonized production and consumption patterns.

Within-country distributional impacts of carbon pricing[3] can be evaluated from different perspectives, i.e., from the point of view of income sources (sources-side), where impacts depend on the emissions intensities of jobs and capital, and from the point of view of expenditures (uses-side), where impacts depend on carbon intensities of consumption baskets (Rausch et al., 2011). Our analysis focuses on uses-side incidence.[4] When looking at within-country uses-side incidence, most household level studies find that distributional impacts are regressive, which stems from the fact that low-income households on average spend larger shares of their budgets on carbon intensive goods and services like energy and food than high-income households (Boyce, 2018; Ohlendorf et al., 2021; Peñasco et al., 2021). Diverging evidence has been found for low-income countries, where carbon price incidence is progressive when low-income households cannot afford carbon-intensive goods and services even without carbon pricing, while high-income households have comparably carbon-intensive lifestyles and would therefore incur relatively higher carbon costs (Boyce, 2018; Dorband et al., 2019; Ohlendorf et al., 2021). When carbon pricing impact on capital is considered, policy impacts tend to be less regressive (Goulder et al., 2019).

Empirical research on the distributional impacts of carbon pricing has been conducted from different perspectives and with different methodological approaches. One body of research analyses climate change accountability questions by matching greenhouse gas emissions at fine sectoral resolution with household expenditure data and computing how carbon emitted along global value chains is linked to the consumption patterns of different household groups. Examples include Chancel (2022) and Ivanova & Wood (2020). These studies rely on input-output methodology, and they benefit from developments in detail and coverage of multi-regional economic and environmental accounts data, namely by EORA and EXIOBASE. The findings of both studies converge in showing how top expenditure quantiles are responsible for a substantially over-proportional amount of global carbon emissions. This is because of their consumption as well as wealth (i.e., investment) profiles (Chancel, 2022).

Absolute carbon footprint statistics by household can provide evidence on which household groups and what products are associated with the largest part of global carbon emissions. They are, however, not sufficient to illustrate the distributional impacts of climate change mitigation policies across households. Indeed, how a carbon price impacts a household group does not only depend on its total carbon footprint but, importantly, on (1) the household group's expenditure on carbon-intensive products relative to its total expenditure, (2) what proportion of these products is covered by a carbon price, and (3) the substitutability of such products with low-carbon or not-carbon-priced alternatives.

Hence, the incidence of carbon pricing policies across household groups has been analyzed by another growing body of research, which we divide into three main categories. In a first category that we denote 'static *direct* incidence simulation', the carbon price is directly applied to household emissions, leading to direct costs for the household. This approach has been used by Andersson & Atkinson (2020) for the Swedish carbon tax on private transport, evaluating tax regressivity over time on the basis of observed household expenditure data and observed carbon tax data. They find that

[3] This paper focuses on within-country incidence. However, between-country incidence may be equally important. Between-country distributional impacts of carbon pricing are connected to whole-economy carbon intensities, where countries relying on carbon-intensive energy and processes are typically hit harder than less carbon-intensive countries (Fullerton & Muehlegger, 2019). A further differentiation can be made between within decile distribution of incidence (horizontal equity) and across decile distribution of incidence (vertical equity), where the former is often found to have a larger variation than the latter (Feindt et al., 2021; Hänsel et al., 2022).

[4] Studies looking at source-side impacts tend to find progressive impacts of carbon pricing (Antosiewicz et al., 2022; Goulder et al., 2019; Mayer et al., 2021)

regressivity of the transport tax depends on whether current expenditure or lifetime expenditure are used as a baseline for the calculation.

In the second category, denoted 'static *total* incidence simulation', a carbon price is imposed on consumers' national or global carbon footprints considering carbon embodied in economic value chains that lie behind those goods and services that households buy[5]. This approach relies on input-output data and methodology, and household expenditure data, as well as assumptions about the carbon price . It has been adopted in several recent studies, focusing on various regions, including low- and middle-income countries (Dorband et al., 2019), Europe (Feindt et al., 2021), the United States (Fremstad & Paul, 2019) and Latin America and the Caribbean (Missbach et al., 2022). Findings suggest predominantly regressive impacts across income groups in Latin America and the Caribbean (Missbach et al., 2022) , regressive impacts across income groups in the U.S. (Fremstad & Paul, 2019), neutral impacts for within-country expenditure groups in the EU (Feindt et al., 2021), and mostly progressive impacts across income groups in other low- and medium-income countries (Dorband et al., 2019). Impacts across expenditure groups across EU countries are found regressive, as low-expenditure households are over proportionally represented in more carbon intensive countries (Feindt et al., 2021). A strength of static incidence analysis is its transparency and reflection of immediate impacts. Dorbrand et al. (2019) argue that immediate impacts are relevant for political acceptability.

Simulations using this approach can include specific price-elasticities of demand, and thereby take basic account of how households would adapt their expenditure in reaction to changed prices. It is also possible to simulate the immediate impacts of different revenue recycling schemes (Fremstad & Paul, 2019). However, static incidence analysis cannot reflect impacts arising from general equilibrium effects, which are especially important to reflect longer term adjustments.[6]

Therefore, a third category of analyses use general equilibrium frameworks, where a larger range of economic adjustments can take place, contingent on the specific set-up of the model. These types of models simulate the outcomes of utility-maximizing behaviour within a given policy setting. Typically, the sectoral resolution is limited and there is a single, representative, agent. General equilibrium frameworks are considered particularly suitable for estimating longer term expected macroeconomic consequences of changed policies, as optimizing adjustment processes may take time. Examples include Rausch et al. (2011) for a general equilibrium simulation of carbon pricing in the United States, Goulder et al. (2019) for a general equilibrium simulation of a carbon tax in the United States, and Sager (2021) for a partial equilibrium simulation of carbon price incidence across the world. All these studies find regressive use-side impacts of carbon pricing, which can be reduced or neutralized by employing revenue recycling schemes.

A common trait observed across simulation studies of all types is the assumption that a single carbon pricing policy is imposed on a single sector (Andersson & Atkinson, 2020) or it is imposed uniformly across all economic sectors (e.g. Feindt et al., 2021; Goulder et al., 2019). While the latter is in line with the economic rationale of incentivizing equal marginal abatement costs across all actors to achieve overall emission reduction at minimal cost, it falls short of real-world implementation to date,

[5] Feindt et al.'s study shows, i.a., how different definitions in spatial scope can imply contrasting results. When household expenditures are grouped by country, impacts are found neutral, and when they are grouped together for the whole EU, impacts are found regressive.

[6] In the long-run, distributional impacts depend on equilibrium effects of carbon prices, which hinge on structural market parameters – particularly price elasticities and the underlying context of substitutability of carbon intensive practices, goods, and services (Fullerton & Muehlegger, 2019). The general rule within an equilibrium setting can be summarized in a simple way: the less price-elastic an agent is compared to other agents, the higher the share of the burden she will bear from the policy. This rule applies to comparisons of demand and supply incidence in a market, but also to discussions of the pass-through of costs in a setting of imperfect competition.

which has been sector-fuel specific. In our analysis, we consider 60 sectors in 54 regions across the world and 270 consumer groups in the EU, within a static total incidence simulation setup, conceptually comparable to Dorbrand et al. (2019), Feindt et al. (2021), Fremstad & Paul (2019) and Missbach et al. (2022). The novelties of our approach compared to the abovementioned studies are fourfold: (1) We use new multi-regional input-output data that is available in yearly time steps until 2021 together with detailed household expenditure data in five year time steps available until 2020, (2) we consider observed heterogenous carbon prices and apply these prices at the production end, (3) we run our analyses across multipletime steps to identify whether distributional impact changes have occurred due to evolving heterogenous price regimes or other factors, and (4) we simulate distributional impacts of an evolving scope of uniform prices, first extending the coverage within countries to all sectors, then to all sectors across countries, with and without domestic revenue recycling.

3. Data & Method

3.1 Matching of Data

Our research is based on the World Carbon Pricing Database (WCPD), the first comprehensive database providing sector-fuel-level carbon prices for the period 1990 to 2021 for 138 countries and several subnational entities (Dolphin & Merkle, forthcoming; Dolphin & Xiahou, 2022). This dataset captures corrective taxation to reduce carbon emissions (see Bruvoll, 2013), and can be used to calculate emissions-weighted, averages of fuel-level, sector-specific, carbon prices, as done in Rafaty & al. (2021). We remap this data and join it with the Global Resource Input-Output Assessment model v.57 (GLORIA), a comprehensive economic accounts framework covering 164 countries with 120 sectors each, across the time span of 1990 to 2020 (Lenzen et al., 2017, 2021). We aggregate the original GLORIA resolution to a 60 economic sector resolution covering 49 countries and 5 Rest of World accounts. We calculate sector-level carbon prices by taking all applicable pricing schemes into account, weighting them with the respective emissions they cover in each sector, and calculating the average. A link between the carbon pricing data and GLORIA is possible because GLORIA includes satellite GHG emissions accounts that provide emissions by IPCC category for each sector.[7] The details of the price-matching procedure are provided in Appendix A.

We then use scientific-use data from the European Household Budget Survey (Eurostat, 2023a) to disaggregate GLORIA household demand vectors into income deciles based on COICOP expenditure classification level 3 (four digit) resolution survey data. The details of this second matching process are provided in Appendix B. As a robustness check, we run our analysis on expenditure deciles as well. [8] We provide disaggregated household demand accounts for all countries and waves that EU HBS scientific use files cover without missing income data.[9] Our sample of countries is given in Table 1.

[7] GLORIA and EORA are the only global input-output time series with carbon emissions disaggregated by IPCC sector we are aware of. We chose GLORIA for its constant sectoral detail, allowing for a detailed matching with household budget survey data, and for temporal decomposition. Further advantages of GLORIA include large country coverage and detailed material and land use satellite accounts, which allow for future extensions of this research.

[8] Grouping households by expenditure deciles rather than income deciles does not change the qualitative differences between the outcomes of our price scenarios in our framework. We therefore conclude that our findings are robust to different definitions of household means.

[9] Carbon prices in 2022 were mostly higher than in 2020, but we do not report incidence results for 2022 in this paper because (a) demand composition might have changed substantially in the course of the global Covid pandemic but we only have pre-Covid household budget survey data, and (b) using 2022 data matched to 2020 household group demand composition does not change the conclusions of the paper.

Table 1: HBS countries and waves with non-missing data in the scientific-use files

Country	*2010*	*2015*	*2020*	*Country*	*2010*	*2015*	*2020*
Austria			*x*	*Latvia*	*x*	*x*	*x*
Belgium	*x*	*x*	*x*	*Lithuania*	*x*	*x*	*x*
Bulgaria	*x*	*x*	*x*	*Luxembourg*		*x*	*x*
Croatia	*x*	*x*	*x*	*Malta*		*x*	*x*
Cyprus	*x*	*x*	*x*	*Netherlands*		*x*	*x*
Czech Republic	*x*	*x*		*Poland*	*x*	*x*	
Denmark	*x*	*x*	*x*	*Portugal*	*x*	*x*	
Estonia	*x*	*x*	*x*	*Romania*	*x*	*x*	
Finland	*x*	*x*		*Slovak Republic*	*x*	*x*	*x*
France	*x*	*x*	*x*	*Slovenia*	*x*	*x*	*x*
Germany	*x*	*x*	*x*	*Spain*	*x*	*x*	*x*
Greece	*x*	*x*	*x*	*Sweden*	*x*	*x*	
Hungary	*x*	*x*	*x*	*United Kingdom*	*x*		
Ireland	*x*	*x*					

In our sample, 37 countries had a carbon pricing in place as of 2020. In most countries, these mechanisms cover GHG emissions from power generation and industry. Only a few countries (e.g., France, Portugal) cover emissions from road transport or buildings. Many of these countries are European countries that participate in the EU ETS. In all countries, the average economy-wide carbon price is below the highest carbon price (Figure 1), reflecting the fact that coverage of emissions is incomplete or that some emissions are faced with a lower price. In 2020, the world average price of CO_2 was USD 2.2/tCO_2. Among countries included in our dataset, the average price of carbon varied between USD 0 and USD 70 in Sweden.

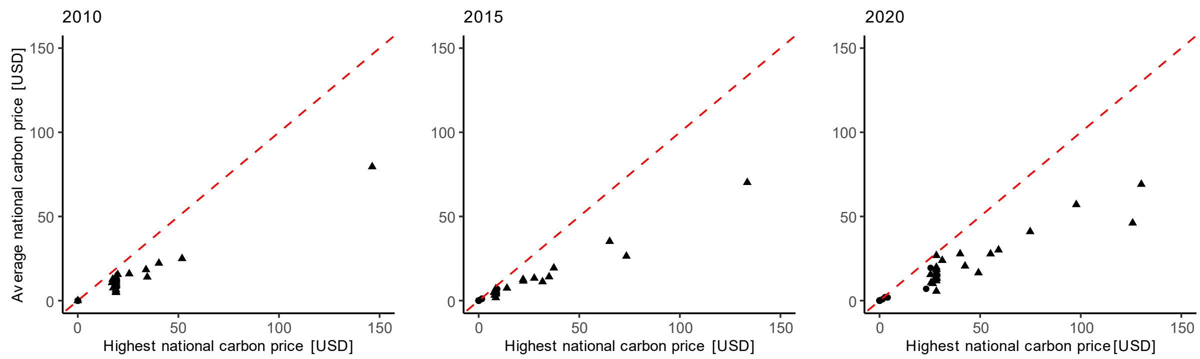

Figure 1: Price variation across 37 countries, plotting for each country the highest sectoral carbon price, and the emissions-weighted average carbon price, post-matching. Triangles for countries that take part in the EU ETS. If the average price is equal to the highest price, triangles are on the diagonal. In most countries the emissions-weighted average is lower than the highest carbon price, due to incomplete emissions coverage.

3.2 Household Incidence

A key feature of our research is to take into account how heterogenous prices at the production level pass through inter-sector linkages to consumers' final expenditure; that is, we do not assume a uniform carbon price applied to carbon footprints, unlike Dorbrand et al. (2019), Feindt et al. (2021), Fremstad & Paul (2019) and Missbach et al. (2022).

The main assumptions of our incidence methodology are (1) carbon prices are applied where emissions are released, generating carbon costs that producers pay, (2) these costs fully pass through international value chains and impact the prices of final consumer products[10]. The sum of all carbon costs at the producer end is therefore equal to the sum of all carbon costs at the consumer end. We furthermore add carbon costs from direct household emissions, where those are subject to a carbon price.

Cost incidence for a household is defined as the proportion of carbon cost over total expenditure. It states what share of a household's expenditure was used to pay for direct and product-embodied carbon emissions. We summarise the approach in the following paragraphs. All vectors and matrices are time-varying, but we omit time indices for easier readibility.

The global economy is represented as a network of economic sectors and final demand. This way of accounting for economic structure and using it for analytical purposes goes back to the work of Francois Quesnay and Wassily Leontief, and is extensively covered by Miller & Blair (2022). Sectors k are interdependent, i.e., they require inputs from each other to generate output. The monetary flows of these interdependencies are captured by the input-output matrix Z with dimension K x K. Consumer demand is captured by a demand matrix Y with dimension K x N, where rows are sectors and columns are consumer groups structured by countries and income or expenditure quantiles. The total output vector is x with dimension K x 1. We have a total number of K sectors, and a total number of N consumer groups. In our case we work with 54 regions, 60 sectors, 10 household groups in 27 EU countries, and aggregated households in all other regions. Therefore, our dimensions are K=3240 and N=297, where K denotes all possible country-sector combinations. The relationships are:

$$\begin{pmatrix} z_{1,1} & \cdots & z_{1,k} \\ \vdots & \ddots & \vdots \\ z_{k,1} & \cdots & z_{k,k} \end{pmatrix} * \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} + \begin{pmatrix} y_{1,1} & \cdots & y_{1,n} \\ \vdots & \ddots & \vdots \\ y_{k,1} & \cdots & y_{k,n} \end{pmatrix} * \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} = \begin{pmatrix} x_1 \\ \vdots \\ x_k \end{pmatrix} \tag{1}$$

We compute the technical coefficients matrix $\mathbf{A}$, which provides input-output coefficients as a proportion of total output[11].

$$\boldsymbol{A} = \boldsymbol{Z} * diag(\boldsymbol{x}^{-1}) \tag{2}$$

The next step is to compute the Leontief matrix $\mathbf{L}$, capturing total input requirements of each sector.

$$\boldsymbol{L} = \boldsymbol{I} + \boldsymbol{A} + \boldsymbol{A}^2 + \boldsymbol{A}^3 + \cdots = (\boldsymbol{I} - \boldsymbol{A})^{-1} \tag{3}$$

In doing so, we account for direct inputs to production, as well as all inputs to inputs. Using total input requirements $\mathbf{L}$ enables us to account for all indirect effects resulting from interconnection of global value chains.

Each sector's output generates CO_2 emissions captured by the vector $\mathbf{e}$. Furthermore, each sector is subject to a specific carbon price, which varies according to what fuels it uses and according to what specific policy provisions are in place. All these industry-specific prices are captured by the vector $\mathbf{p}$.

[10] The extent to which carbon prices pass-through value chains is an active field of research and empirical studies find large variation in pass-through rates between -300% and + 300% for the EU-ETS (Neuhoff & Ritz, 2019). It is possible that actual pass-through rates vary across scenarios. To ensure ceteris paribus scenario comparability, we stick to full pass through in this project. The variation of cost pass through and carbon price incidence in an input-output setting is left for future research.

[11] Cases of zero output are denoted by elements of $\mathbf{x}$ being equal to zero. Such cases return errors when computing the inverse of elements of $\mathbf{x}$. We therefore impose:

$$\boldsymbol{x}^{-1} = \begin{cases} \boldsymbol{x}^{-1} & for\ vector\ elements\ x_k \neq 0 \\ 0 & otherwise \end{cases}$$

From $\mathbf{e}$ and $\mathbf{p}$, we compute the total carbon costs $\mathbf{c}$, which occurs at the production end, as well as the direct carbon cost intensities $\mathbf{d}$ of production.

$$\boldsymbol{c} = diag(\boldsymbol{e}) * \boldsymbol{p} \tag{4}$$

$$\boldsymbol{d} = diag(\boldsymbol{x}^{-1}) * \boldsymbol{c} \tag{5}$$

With our direct cost intensities $\mathbf{d}$ and our Leontief matrix $\mathbf{L}$, we compute the type 1 multiplier[12] for carbon costs, which we denote $\mathbf{m}$. $\mathbf{m}$'s dimension is 1 x K.

$$\boldsymbol{m} = \boldsymbol{d}^T * \boldsymbol{L} \tag{6}$$

To calculate the carbon costs embodied in consumption bundles, i.e., the indirect carbon cost (icc), we pre-multiply the consumer group's consumption bundle $\mathbf{y_i}$ with our multiplier.

$$icc_i = \boldsymbol{m} * \boldsymbol{y_i} \tag{7}$$

Incidence, rcc, is given by the consumer carbon costs divided by total expenditure on products from all country-sector combinations. This indicator captures the consumer burden from carbon pricing as an indirect form of taxation.

$$rcc_{emb_i} = \frac{icc_i}{\sum_k y_{ki}} \tag{8}$$

We furthermore add the direct household carbon emissions and associated direct household carbon costs. For this step we use the household emissions vector $\mathbf{h}$ and the emissions weighted carbon prices for household emissions $\mathbf{p}$.

$$dcc_i = \boldsymbol{h_i}^{\boldsymbol{T}} * \boldsymbol{p} \tag{9}$$

Incidence is given accordingly, providing an indication of the consumer burden from carbon pricing as a direct form of taxation.

$$rcc_{direct_i} = \frac{dcc_i}{\sum_k y_{ki}} \tag{10}$$

and incidence of all carbon costs is then:

$$rcc_{full_i} = \frac{icc_i + dcc_i}{\sum_k y_{ki}} \tag{11}$$

The average carbon price paid by consumers is calculated in in a similar fashion as incidence, but we replace the denominator by the total carbon footprint of the respective household group.

3.3 Distributional Indicators

To compare distributional implications of varying price regimes we compute a summary measure of the distributional impacts, the Suits Index. The Suits index is a measure of progressivity of tax, comparable to the Gini index for income and wealth distribution, and is commonly used in the literature (Andersson & Atkinson, 2020; Feindt et al., 2021). It is defined on the interval [-1,1]. If carbon costs accumulate faster than income over the range of income quantiles, the suits index is negative, implying a regressive policy impact. If income accumulates faster than costs, the suits index is positive,

[12] Input-Output modelling literature makes a distinction between Type I and Type II multipliers. Type I multipliers reflect direct and indirect effects, while Type 2 multipliers also include induced effects. The latter requires endogenizing demand vectors, for which various methods exist (Emonts-Holley et al., 2021). Both environmental footprint analyses and IO-based incidence analyses are based on Type 1 multipliers.

implying a progressive policy impact. Therefore, values below zero indicate regressive tax impact, and values above zero indicate progressive tax impact, and zero indicates a neutral impact.

The index is calculated by relating the area under a Lorenz curve to the area under a hypothetical diagonal of perfectly equal distribution (Suits, 1977):

$$S = 1 - \frac{L}{\frac{1}{2} * 100^2} \tag{12}$$

where L is the area under Lorenz curve that relates accumulated percent of expenditure y to accumulated percent of total tax burden T. It is calculated as:

$$L = \int_0^{100} T(y)\, dy \tag{13}$$

If the whole tax burden falls on the poorest household, then $L = 100^2$ and hence $S = -1$. If it only falls on the richest household, then $L = 0$ and hence $S = 1$. If the tax burden is proportional to y, then $L = \frac{1}{2} * 100^2$ and hence $S = 0$. In the case of aggregated household groups i, for example deciles, we can use a trapezoidal approximation to the continuous integral:

$$L_{apprx} = \sum_{i}^{10} \frac{1}{2} * \left(T(y_i) + T(y_{i-1})\right) * (y_i - y_{i-1}) \tag{14}$$

As a second distributional indicator we use the tax incidence ratio of the lowest income decile over the highest income decile:

$$p10p90 = \frac{rcc_1}{rcc_{10}} \tag{15}$$

This indicator has an intuitive interpretation, showing how much larger the burden on low-income households is compared to the burden on high-income households.

3.4 Structural Decomposition of Incidence Factors

Given that our data spans multiple time steps, we can decompose changes in consumer incidence into different factors. This allows us to find out how price changes have impacted different consumer groups, and how these impacts compare to other factors of incidence. While earlier studies on inequality and climate policy have applied cross-sectional decompositions (Dorband et al., 2019; Feindt et al., 2021), we decompose changes over time using Structural Decomposition Analysis (SDA). The idea is to disentangle the observed change in an aggregate variable of interest into its constituent factors.

SDA is the input-output model equivalent to index decomposition analysis (IDA), and it is preferable to the latter due to its ability to handle indirect effects, i.e., in our case indirect tax effects. It is a well-established method in research on energy and carbon emissions and available SDA methods have been reviewed extensively (de Boer & Rodrigues, 2020; Hoekstra & van den Bergh, 2003; Rose & Casler, 1996; Su & Ang, 2012). In our study we use the Log Mean Divisia Index (LMDI) as a decomposition formulation[13]. It goes back to the Montgomery price and quantity indicators, and has

[13] Ang & Choi (1997) and Ang & Liu (2001) are commonly referenced papers in the field of environmental and energy research. We correct for zero-value problems using an algorithm suggested by Wood & Lenzen (2006). A comparable LMDI application to input-output time series was done by Wachsmann et al. (2009), who decompose energy use in Brazil.

the advantages of being non-parametric and leading to a unique solution without residual (De Boer, 2008).

We decompose incidence rcc by consumer group and country into seven factors, namely emissions intensities $\mathbf{e}$, carbon prices $\mathbf{p}$, economic structure $\mathbf{L}$, consumption bundles $\mathbf{y}$, total scale of consumption a, household emissions $\mathbf{h}$, and prices on household emissions $\mathbf{k}$. As derived in section 3.2, the identity is given by:

$$rcc = (diag(\boldsymbol{e}) * \boldsymbol{p})^T * \boldsymbol{L} * \boldsymbol{y} * a^{-1} + \boldsymbol{h}^T * \boldsymbol{k} * a^{-1} \tag{16}$$

We decompose the change in carbon costs between two timesteps, t=1 and t=0, into:

$$\Delta rcc = \Delta rcc(\boldsymbol{e}) + \Delta rcc(\boldsymbol{p}) + \Delta rcc(\boldsymbol{L}) + \Delta rcc(\boldsymbol{y}) + \Delta rcc(a) + \Delta rcc(\boldsymbol{h}) + \Delta rcc(\boldsymbol{k}) \tag{17}$$

Where $\Delta rcc(\boldsymbol{e})$ is the change in rcc due to $\boldsymbol{e}$, holding all other factors fixed. This allows us to isolate the effect of a single factor on the change, holding all else equal. Its derivation is based on expressing the integrated total differential of the equation as the sum of all integrated partial differentials. Importantly, this process relies on the assumption that factors are independent. Using the LMDI formulation, the contribution of changing carbon prices is:

$$\Delta rcc(\boldsymbol{p}) + \Delta rcc(\boldsymbol{k}) = \sum_{no} \frac{\Delta(e_n p_n L_{no} y_o a^{-1})}{\Delta(\ln e_n p_n L_{no} y_o a^{-1})} * \ln \frac{p_n^1}{p_n^0} + \sum_{v} \frac{\Delta(h_v k_v a^{-1})}{\Delta(\ln h_v k_v a^{-1})} * \ln \frac{k_v^1}{k_v^0} \tag{18}$$

We provide the remaining decomposition formulas and the derivation of structural decomposition with the LMDI approach in Appendix C.

3.5 Scenario Simulation

Finally, we compare household incidence of the observed heterogenous carbon prices with hypothetical uniform price scenarios for each country and year. With each scenario we increase the scope of uniformization, adjusting the price vectors accordingly. In scenario 2, we only adjust prices within the country of interest. In scenario 3, we adjust prices in the EU ETS region plus Switzerland. In scenarios 4 and 5 we adjust prices in all countries of the world. Scenarios and interpretations are summarised in Table 2.

Table 2: Scenarios[14]

Name	*Description*
S1 Existing	*The baseline of heterogenous policies as observed. Household incidence is affected by domestic policies as well as foreign policies where these policies affect imported products.*
S1b Existing w/o non-EU	*The baseline of heterogenous policies as observed, but with prices in non-EU countries set to zero.*
S2 Uniform within country	*Alternative scenario. We identify a uniform carbon price that would return the same total revenue as the heterogenous baseline and impose it on all sectors equally. We leave pricing policies in other countries as they are.*
S3 Uniform across EU	*Alternative scenario. We take the EU ETS price and apply it uniformly across all sectors in all countries within the EU ETS region. Pricing policies in other countries stay as they are.*
S4 Uniform across world	*Alternative scenario. We take a price of USD 50 and apply it uniformly across all sectors in all countries. This is the lower bound recommended by the High-Level Commission on Carbon Prices*
S5 IMF CPF	*Alternative scenario. We impose the IMF Carbon Price Floor scenario, implying USD 25 for low-income countries, USD 50 for medium-income countries, and USD 75 for high-income countries, applied uniformly across sectors.*

[14] We have run more scenarios than those stated in this table, but we only report the main scenarios in this paper. Examples for further scenario variations we have analyzed include different S2 scenarios, choosing uniform prices according to the average price or according to the highest price. In most cases this variation made no substantial difference. We have also run explicit EU CBAM scenarios, finding progressive impacts.

After running all scenarios without explicit consideration of what happens with the revenues generated through the pricing policies, we introduce revenue recycling as a last step in our analysis. We choose a lump sum transfer scheme, where all carbon pricing revenues generated within a country are redistributed equally across the population within the same country.

4 Results

4.1 Heterogenous Carbon Price Incidence

This section discusses results for carbon prices as implemented by countries so far (i.e., the 'baseline'). Explanations are further elaborated as we move through the following sections. Our analysis shows that the average incidence of these prices was generally low, ranging between 0.1% of household expenditures in Luxembourg in 2015 and 1.9% in Estonia in 2010. The decile-wise distribution across EU countries is illustrated in panel A of Figure 2. In all the 19 EU countries for which we have detailed expenditure data for 2020, carbon pricing incidence was regressive, implying that lower-income households incurred a larger relative expenditure burden from carbon pricing than high-income households. For 2020 we find the largest difference in incidence in Estonia, where first income decile spent three times more of their budget than the tenth income decile.

Two factors drive the carbon cost. The first factor driving incidence of carbon pricing is the carbon content of consumption bundles, calculated by dividing the amount of carbon embodied in consumption by total expenditure (Figure 2, panel B). The average carbon footprint per USD spent provides an indication of the incidence of a uniform carbon price on consumer groups, all else equal. Our results for this indicator confirm a well-established finding in the literature: In countries of the global north, lower-income groups spend a higher proportion of their budget on carbon intensive products, like gas for heating, while high-income groups spend a lower proportion of their budget on such products. Importantly, high-income households still have larger absolute carbon footprints than low-income households, but this does not imply a high relative burden of carbon pricing.

Many countries in our sample have a slightly inverted u-shaped carbon intensity of expenditure across income groups. This means that the first income decile can still have a comparably low carbon intensity of expenditure, while the next deciles have comparably high intensities. Reasons include that first and second income deciles have lower expenses on petrol, associated with less car ownership. From the fourth decile onwards, intensities decrease again. For 2020 we observe the highest intensities in Bulgaria and Estonia, where carbon intensities range between 400 and 1000g CO_2 per USD, and the lowest intensities in Denmark and France, where carbon intensities range between 150 and 250g CO_2 per USD. We find a general tendency for increased regressivity with increased carbon intensity of the economy. This tendency is significant for 2015 and 2020 when regressivity is measured with the p10p90 index: we observe an increase of 0.4 – 0.5 in p10p90 for every 100g increase of carbon intensity. A complete overview on regressivity correlations is provided in Appendix D.

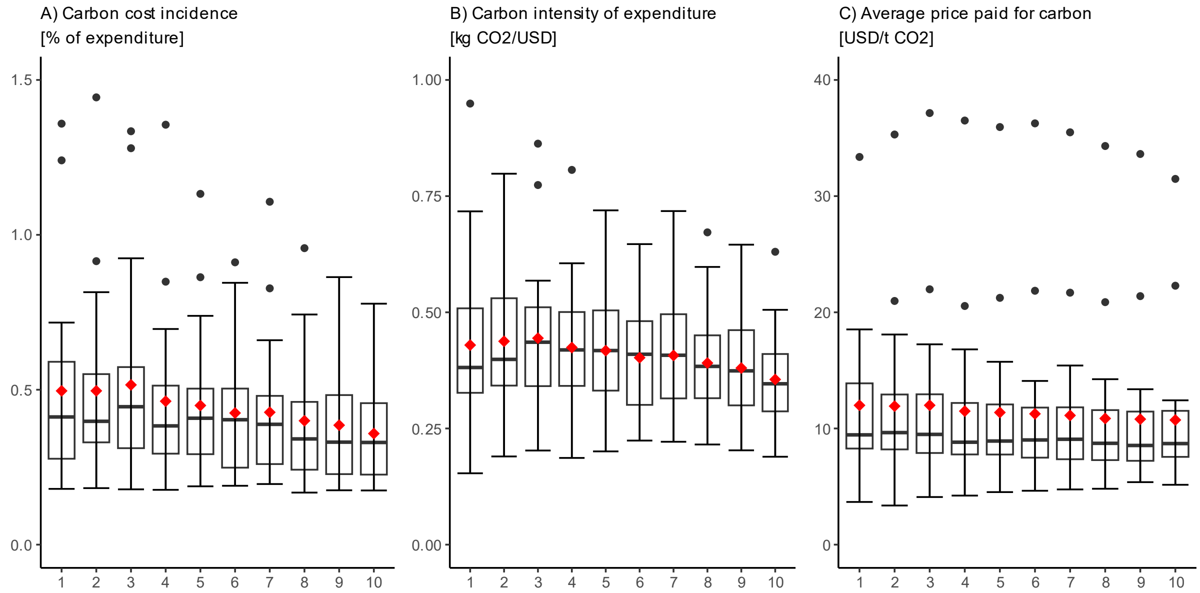

Figure 2: Carbon price incidence by income decile in 2020. Distributions across EU countries, excluding Czech Republic, Finland, Ireland, Poland, Portugal, Romania, Sweden and United Kingdom due to missing data in the 2020 wave of the European Household Budget Survey. Red dots are distribution means. Panel C shows the average price that the household group paid per ton of carbon. Panel B shows the average emissions intensity per USD of expenditure of the household group. Panel A shows the incidence of costs from carbon pricing on the household group's total expenditure. In each panel we move across within-country income-deciles from left to right.

Due to non-uniform carbon prices across sectors, the price of carbon embodied in different products varies. Products that result from value chains which are mostly covered by carbon pricing policies will have a larger embodied carbon price than products resulting from value chains that are less comprehensively covered by carbon pricing policies. As consumption bundles vary across household income groups, the heterogenous nature of carbon prices has implications for incidence. This is the second factor of incidence (Figure 2, panel C). Household groups consuming a larger proportion of non-priced goods and services benefit from the price heterogeneity, while those groups that consume a larger proportion of priced goods and services face a higher implicit carbon price on average.

Our incidence calculations for the EU in 2020 show that average price paid for carbon across all emission sources were around 11.35 USD, which was 60% lower than the EU ETS price of that year (28.22 USD). The difference between this average price paid for carbon and the EU ETS price is due to incomplete carbon price coverage in the value chains behind the products that EU consumers buy. Similarly, in countries that have adopted a carbon tax in addition to the EU ETS, we also find lower average price paid for carbon than the maximum national carbon price. In France, for example, the average price paid was 34.95 USD in 2020, while the carbon tax in the same year was 50.87 USD.

Our results show that the heterogeneity in carbon prices has on average led to higher average prices paid for carbon for low-income household groups than for high-income household groups. On average, the first income deciles paid 1.26 USD more per ton of carbon than the tenth income decile. We observe the largest difference in carbon rates for Bulgaria, where the lowest income decile paid 4.95 USD more per ton of carbon than the highest income decile. Differences also prevail in large economies such as Germany, where households belonging to the first income decile paid 1.76 USD more per ton of carbon than households belonging to the tenth income decile. The exceptions in 2020 are Denmark, Lithuania, Luxembourg, and Spain, where the highest income households faced a higher price than the lowest income households.

4.2 Temporal Decomposition of Incidence

Our decomposition of incidence changes over time shows that, as a result of decreasing carbon intensities, household incidence overall is lower in 2020 than in 2010. However, it increased between 2015 and 2020, largely due to increasing product-embodied carbon prices, whose effect was only partly offset by decreasing carbon intensities. Increasing prices from 2015 to 2020 occurred in line with the increasing EU ETS price from 8.52 USD to 28.24 USD. The downward push from carbon intensities occurs in line with efficiency improvements, which, all else equal, lowers the carbon cost burden on households as it reduces the carbon footprint of products that households buy. Demand composition changes mitigated incidence to a small extent, reflecting the small adaptation of consumers consumption bundles. Importantly, our decomposition methodology does not allow for causal inference – we are unable to assert if demand composition would have changed more under a more stringent pricing regime.

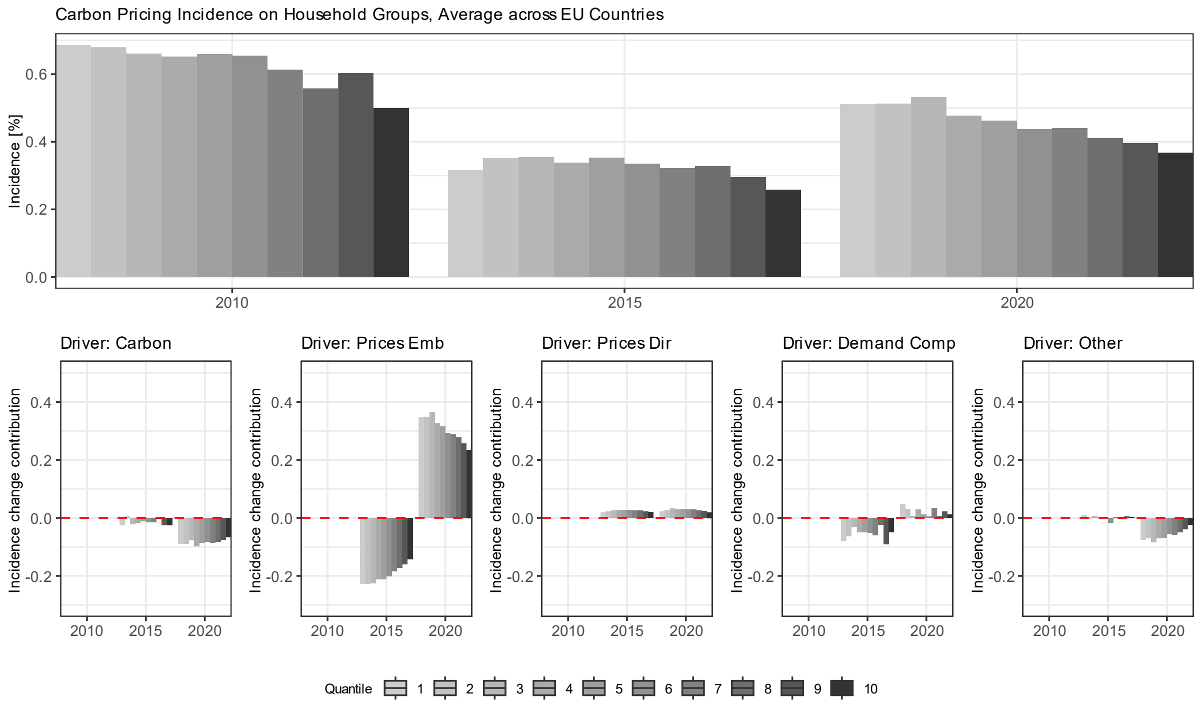

Figure 3: LMDI structural decomposition results. We decompose the change from 2010 to 2015 and the change from 2015 to 2020 into contributions from its underlying factors. Factors are: carbon intensity (Carbon), product-embodied prices (Prices Emb), direct household emission prices (Prices Dir), composition of consumption bundle (Demand Comp) and demand volume and technical coefficients, which are collected in an "Other" category. The top panel shows incidence as observed. The bottom panels show what the year-to-year change would have been if it had been the outcome of a respective factor only. Bars below zero imply that the factor contributed negatively (reducing incidence), bars above zero imply that the factor contributed positively (increasing incidence).

Regressivity of household incidence has mostly been driven by product-embodied carbon prices, as the lower second panel of Fig. 3 indicates. Bars are longer for the lower income deciles than for the higher income deciles, suggesting that this factor has increased incidence more for low than for high income groups. Carbon prices on direct household emissions, carbon intensities, and demand compositions did not have strong distributional incidence implications on average.

4.3 Incidence Impacts of Uniform Prices

To understand how household incidence regressivity is related to the heterogenous nature of carbon prices observed, we calculate country-decile-wise the household incidence of alternative carbon pricing scenarios where the carbon price is applied uniformly across emissions sources; that is, we ask what the household impact would have been with less heterogeneity in prices.

To summarize the regressivity in a country we use the Suits Index, which we introduced in the method section. The Suits Index compares the accumulation of policy-induced carbon costs across household groups to the accumulation of income across household groups. The first alternative scenario we consider is where every country imposes a uniform carbon price on its domestic emissions. The magnitude of the price is chosen so that the total revenue generated from the pricing scheme is equal to the revenue that was generated under the heterogenous pricing baseline. Consequently, this scenario leaves the fiscal implications of carbon pricing unchanged compared to the baseline scenario. Results provide a mixed picture yet show a tendency of uniform carbon levies to mitigate regressivity impacts. In 2020, 15 of the 19 countries in our sample would have had a less regressive incidence under uniform carbon prices compared to the heterogenous carbon pricing baseline. In addition, we find a significant correlation between the regressivity-mitigating impact of a uniform price and GDP/capita of a country, suggesting that a uniform price reduces regressivity particularly in lower-income EU countries (see Appendix D).

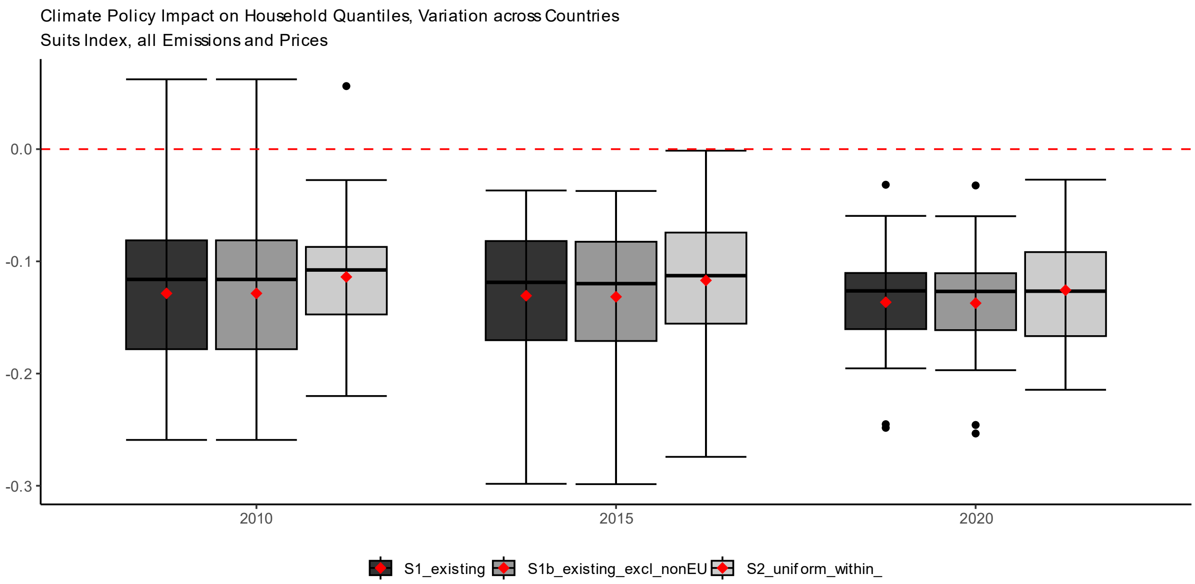

Figure 4: Suits index variation across countries, comparing prices as observed (S1) with a domestic price uniformization scenario (S2). Red dots are means across countries. S1b makes hardly any difference to S1, which indicates that observed carbon prices outside of the EU have hardly had any distributional impacts. A negative suits index implies regressive impacts, a positive suits index implies progressive impacts. Notice how uniform prices make impacts less regressive.

In the next scenarios, we gradually increase the regional scope of carbon price uniformization. In scenario 3, we assume that the EU ETS is applied to all sectors in all countries that participate in the EU ETS area plus Switzerland. On average across countries, this scenario again implies less regressivity (as measures by the Suits index) than the heterogenous pricing baseline, although to a smaller extent than in scenario 2. In 68% of the countries in our sample for 2020 scenario 3 leads to less regressivity. These countries are the same as those for which find regressivity-mitigating impacts in scenario 2.

Scenario 4 is a global uniform price scenario, where a carbon price of 50 USD is applied globally across all sectors and regions. This scenario provides the lowest magnitude Suits index of all scenarios, implying that incidence impacts for EU households are the least regressive, partly due to the fact that higher-income households consume relatively more imported goods. We return to this discussion below. In most of the countries of our 2020 sample (except Denmark, Spain, Lithuania and

Luxembourg) a global uniform price would have reduced regressivity of household incidence. We observe the largest regressivity change in this scenario for Bulgaria, Cyprus, and Malta, where regressivity measured by the Suits index is reduced by between 34% and 62%.

The last scenario we consider is the IMF carbon price floor scenario, where low-income countries are subject to a uniform price of 25 USD per ton of carbon, middle-income countries are subject to 50 USD per ton of carbon, and high-income countries are subject to 75 USD per ton of carbon. This scenario implies less regressivity than both the heterogenous baseline (scenario 1) and price uniformity across the EU (scenario 3), but not as little as the global uniform price (scenario 4).

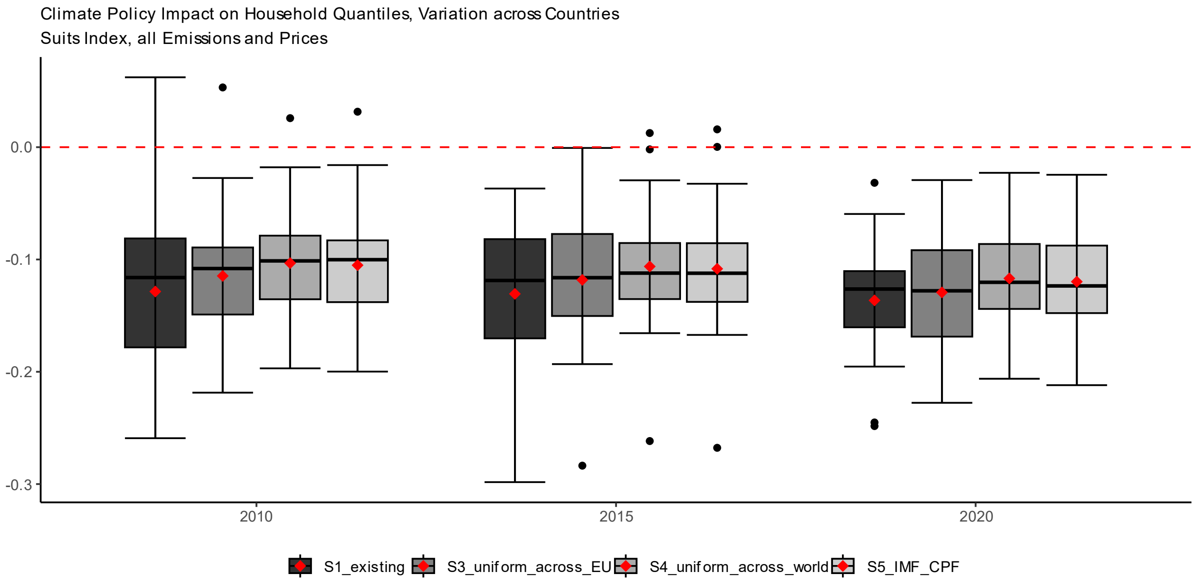

Figure 5: Suits index variation across countries, comparing prices as observed (S1) with EU-wide price uniformization (S3), global price uniformization (S4) and the IMF carbon price floor scenario (S5). A negative suits index implies regressive impacts, a positive suits index implies progressive impacts. Notice how uniform prices make impacts less regressive.

The driving forces behind the regressivity-mitigating impact of price uniformization can be illustrated in two ways. The first relates to the average price paid for carbon, as illustrated in panel c) of Figure 2. In our analytical framework the average price paid for carbon at the household end is the main endogenous variable that changes when we impose counterfactual pricing scenarios. Therefore, it explains a large part of the distributional differences we observe across scenarios. To isolate the distributional consequence of this driver, we compute the difference in price paid for carbon between the lowest (D1) and highest (D10) decile of the income distribution. Figure 6 shows that harmonizing carbon prices within countries (S2 central panel), and even more so across all countries (S4 right panel) would reduce this difference, thereby mitigating the regressive impact of carbon pricing all else equal.

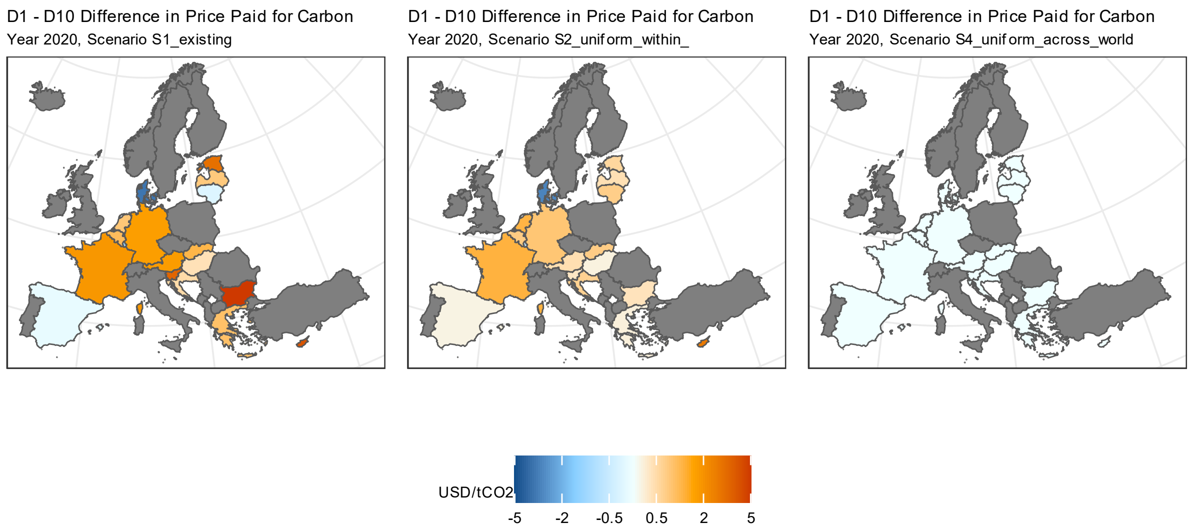

Figure 6: Difference in price paid for carbon. Household budget survey data is missing for some country-year entries (see Table 1). Hence the indicator presented in the figure may not be available for all countries or years (greyed-out countries).

Second, we look at disaggregated accounts of incidence for a selected country. In Figure 7 we compare the disaggregated incidence of the heterogenous pricing baseline with our domestic price uniformization scenario (S2) and global price uniformization (S4) for Bulgaria and for Denmark. The explanation for the impact in Bulgaria is as follows. Lower-income households spend an overproportionate share of their budget on electric power, which is covered by a carbon price already in the baseline, due to EU ETS. As we switch to domestic price uniformization, the previously exempted sectors get covered by a carbon price and the previously covered sectors are subjected to a slightly lower carbon price than before. This is because, by assumption in the uniformization scenario, the fiscal impact (revenue) of all carbon prices is held constant, not the prices themselves. This implies that transport service, household mobile emissions, and household residential emissions become more expensive. Both transport service emissions and emissions from driving cars are categories that hit high-income households more than low-income households in Bulgaria, and this leads to less regressive pricing incidence overall.

In Denmark the difference in consumption bundles across household groups is smaller than in Bulgaria, and the different sectors of the economy are already relatively comprehensively covered by a carbon price, as manufacturing is covered by EU ETS, and service sectors are covered by a national carbon tax. Price uniformization therefore implies no large incidence difference in countries like Denmark.

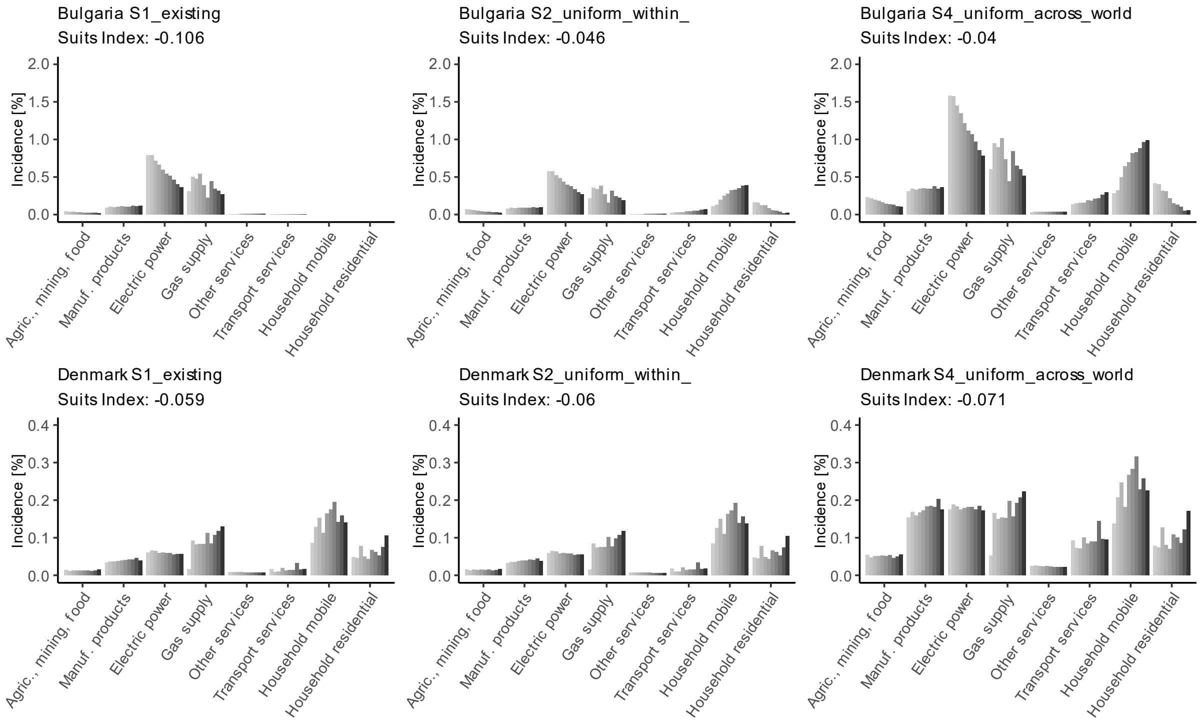

Figure 7: Disaggregated household incidence of carbon pricing in Bulgaria (top row) and Denmark (bottom row). Notice how electric power in Bulgaria is always regressive, throughout scenarios. Grouped bars relate to income groups, where the lightest grey is the first decile, and the darkest grey is the last decile. Incidence is defined as the proportion of carbon costs over total expenditure, for each income decile. The first column displays baseline scenario results, the second column displays the result of domestic price uniformization, the third column displays the result of global price uniformization.

The dynamics that explain the differences between scenarios where we vary prices abroad (i.e., in non-EU countries), for example S4, also have clear explanations. Our data suggests that high-income households spend a larger proportion of their budgets on products that result from international value chains, compared to low-income households. In scenarios S3 to S5, carbon prices applicable abroad are increased and applied uniformly across economic activities. The implication is that products relying on international value chains, as well as directly imported products, become more expensive, which hits high-income households over-proportionally. The last column in Figure 6 provides a disaggregated example for Bulgaria and Denmark. Two consumption categories that push incidence towards progressivity in both cases are manufactured products, i.e., physical products such as smart devices, clothes, shoes, and transport services including air and water transport. In the case of Bulgaria, increased regressivity through more expensive food and energy is balanced out by the progressive impact through transport and manufactured products.

To examine general tendencies of scenario impacts, we run pooled regressions of the differences between our alternative scenarios (S2-S5) and the baseline scenario (S1) on different economic characteristics of the countries in our sample. Results for the S1-S4 difference are reported in Table 3 and results for all other scenario differences are reported in Appendix D. We find that the regressivity-mitigating impact of a uniform price significantly decreases with GDP per capita. This implies that uniform prices would have lowered regressivity particularly for EU countries that have a comparably lower level of GDP per capita.

Table 3: Explaining scenario differences across countries. We estimate linear models to evaluate whether scenario impacts vary with country characteristics. Our dataset covers 27 countries and three years. The dataset is unbalanced due to missing Eurostat data, as reported in table 1. Coefficients are estimated using pooled OLS and cluster-robust standard errors.

	S1 – S4 Difference in Suits					*S1 – S4 Difference in P10P90*				
Intercept	*0.356*	*0.102*	*0.001*	*0.027*	*0.029*	*-2.642*	*-0.837*	*-0.018*	*-0.238*	*-0.258*
	(0.128)	*(0.083)*	*(0.012)*	*(0.007)*	*(0.006)*	*(0.863)*	*(0.750)*	*(0.108)*	*(0.060)*	*(0.061)*
Log GDP/capita	*-0.032*					*0.234*				
	(0.012)					*(0.083)*				
Log Population		*-0.005*					*0.041*			
		(0.005)					*(0.045)*			
Carbon intensity [100g/USD]			*0.073*					*-0.955*		
			(0.059)					*(0.620)*		
m_price [USD]				*-0.000*					*0.003*	
				(0.000)					*(0.002)*	
h_price [USD]					*-0.000*					*0.003*
					(0.000)					*(0.001)*
DF	*65*	*65*	*65*	*65*	*65*	*65*	*65*	*65*	*65*	*65*
R^2	*0.18*	*0.05*	*0.04*	*0.01*	*0.04*	*0.12*	*0.04*	*0.08*	*0.03*	*0.06*

Differences between countries of varying GDP per capita are related to how consumption bundles vary across household groups, for example, expenditures on personal transport. In low GDP per capita countries such as Bulgaria, pricing household mobile emissions is progressive and so a uniform price that covers household mobile emissions hits high-income households that faced a lower burden in the baseline. In a high GDP per capita country such as Luxembourg, the shift towards pricing household mobile emissions is regressive, as poorer households spend an overproportionate share of the expenditure on personal transport. In general terms: Products that have benefited from carbon price exemptions in the empirical baseline tend to have been luxury products in lower-income EU countries and basic products in high-income EU countries.

4.4 Revenue Recycling

As a last step in our incidence analysis, we include revenue recycling in all our scenarios. The mechanism we apply is a lump-sum redistribution system, according to which all fiscal income generated from carbon pricing policies applied on domestic sectors are redistributed equally across households within the country at hand. In a closed economy, such a mechanism would imply that the carbon costs across household groups add up to zero. Those groups who emit above proportion would incur a net positive cost. Those groups who emit below proportion would incur a net surplus, meaning negative cost, as the lump sum transfer exceeds the money spent on paying for carbon.

In open economies such as those of EU countries where consumers buy products that are imported as well as domestic products that result from international value chains, the total carbon costs paid by households are not equal to the carbon costs that accumulate in domestic sectors. As soon as household expenditure bundles are affected by production abroad that is subject to lower carbon prices than those applied domestically, the carbon pricing revenue collected domestically may exceed the carbon costs that households are incurring through their consumption of products. In our analysis, these dynamics play a dominant role.

The main finding is that in all EU countries in 2020 in the baseline scenario, carbon costs for the lower-income household groups become net negative, implying that the redistribution mechanism returns more money to these households than the costs they incur from carbon pricing. In most EU countries all household groups have net negative carbon costs. The exceptions with positive carbon costs are the richest decile in France, in Greece, and in Lithuania, the richest two deciles in Latvia, the richest three deciles in Denmark, and the richest five deciles in Luxemburg. As soon as we price carbon uniformly across the globe, all tenth decile household groups with the exception of Estonia, have positive carbon costs, but the lower-income household groups continue to receive more revenue than their incurred costs.

We also find, consistent with existing literature (e.g. Feindt et al., 2021; Fremstad & Paul, 2019), that lump sum redistribution of domestic carbon pricing revenue makes policy impacts progressive. This is the case for all EU countries in our sample, and it holds for all the timesteps we consider.

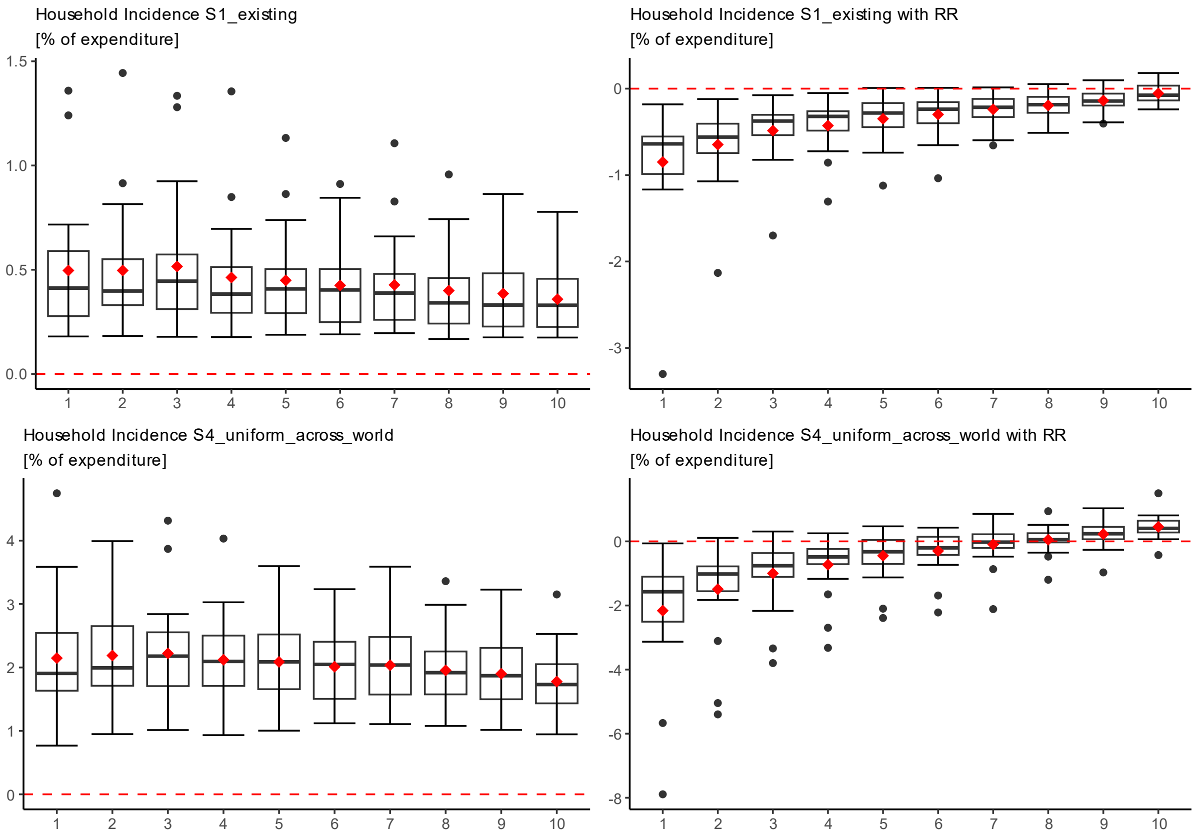

Figure 8: Comparing household incidence for income deciles in scenario 1 (top row) and scenario 4 (bottom row) without revenue recycling (left column) and with revenue recycling (right column). Boxplots display distributions across EU countries in 2020. Red dots signify averages. Note that when introducing revenue recycling in scenario 1, the incidence for all households through decile 6 become negative, implying a negative cost burden, e.g. households are better off due to the carbon price. Negative carbon costs under revenue recycling happen due to the fact that we have open economies, where carbon prices incidence passes through to households outside of the EU as well, while revenue is redistributed within countries.

5 Discussion

The research we present in this paper is based on an environmentally extended global input-output framework, which is available as a time series. We simulate baseline and alternative scenarios *ex-post*, asking how historical incidence of carbon pricing would have differed with more uniform policies and with earmarking of revenues for uniform lump sum redistribution. The availability of multiple years in the household expenditure microdata and economic accounts data allows for incidence calculations for multiple time steps, which embed changing expenditure bundles, carbon prices, technology, and technical coefficients.

Consistently across all time steps we find that uniformization of carbon pricing tends to lead to more neutral distributional incidence, and lump sum revenue recycling makes incidence progressive in all cases. Furthermore, our structural decomposition suggests that incidence has both increased and become more regressive from 2015 to 2020. Both these developments can be attributed to changing carbon prices, rather than changing expenditure or changing technology and technique. These findings highlight the value of working with yearly input-output time series, and they respond to a research gap identified by Feindt et al. (2021).

Our results add a distributional argument to the efficiency argument for a uniform marginal cost of pollution. Indeed, exemptions and rebates as observed between 2010 and 2020, and often introduced to accommodate political economy constraints, led to regressive effects of carbon pricing. In other words, on the expenditure side in EU countries, heterogeneity in carbon prices has made incidence more regressive than what would have been observed in the case of a uniform price.

Overall, the magnitudes of our estimates of the cost burden as a share of household income (i.e., incidence) appear generally low, and they are lower than those estimated by Feindt et al. (2021). One difference is that our price data considers exemptions, which leads to lower estimated incidence than when assuming highest prices. Given that our price data does not take into account free allocation of EU ETS allowances, it is likely that the actual costs of emitting carbon for EU-ETS covered industries were even lower than what we calculated with. Therefore, we should consider scenario 1 as an upper bound estimate of what incidence actual was. Our scenario 4, which assumes a uniform price across the world, should provide results that are comparable to other studies that adopt uniform prices. Our incidence estimates are also lower than those obtained in research on household incidence of energy taxation. For instance, Amores et al. (2022) find that the average incidence of housing energy taxation in EU countries is 4 percent on first decile households, and 1 percent on tenth decile households.

A strength of our analysis is that we capture all indirect pricings effects. Earlier incidence studies have attributed carbon price regressivity to consumption bundles and emission intensities only. We contribute to this discussion by showing that price variation is an additional factor that in the case of EU countries has increased regressivity on average. Furthermore, our study highlights the importance of considering inter-regional-inter-sector linkages in climate policy evaluation. The largest part of incidence changes for EU households from 2010 to 2020 is explained by prices passing through product value chains. As EU economies are very open to international trade, prices outside of the EU have impacts on industry and households within the EU, and prices within the EU can affect EU exports. For the 19 EU countries in our 2020 sample, we find that the total carbon costs for consumers were 35% lower than the carbon costs at the production end in the same sample. Average consumer carbon prices tend to be lower than the carbon prices applied to domestic sectors, simply because the end products for consumption result from international value chains. Some of these dynamics have been analysed for the case of Germany in a general equilibrium setting by Böhringer et al. (2021).

Two current climate policy developments in the EU appear distributionally progressive against the findings of our research. The first is the extension of carbon pricing to more sectors through the EU ETS II, which will be launched in 2027 (European Commission, 2023c). This extension is close to our EU ETS extension scenario (S3), except for the fact that the price level we assume is lower than the price ceiling enshrined in the legislation (EUR 45/tCO_2). The second is the introduction of the EU Carbon Border Adjustment Mechanism (CBAM) entering into force in 2026 (European Commission, 2023a). This mechanism will ensure that specific high-carbon-intensity imported products will be subject to the same carbon price as the inner-European EU ETS, which reduces the gap between carbon prices of domestic products and imported products. As suggested by our scenario 4, the alignment of carbon prices internationally has progressive incidence for most countries within the EU. We therefore expect that EU ETS 2 and EU CBAM will not only improve economic efficiency, environmental effectiveness, and international carbon leakage risk, but also reduce regressivity of carbon pricing in the EU.

The results of this analysis must be read keeping its limitations in mind. First, similar to comparable analyses by Dorband et al. (2019) Fremstad & Paul (2019) and Missbach et al. (2022), we do not model demand adjustments in our alternative scenarios. This does not have implications for our baseline scenario, in which case substitution effects from policies in place have already taken place. However, in the alternative scenarios, one could expect a demand response to changing prices, at least in the medium- to long run. Yet, this is unlikely to lead to different qualitative results. Feindt et al. (2021) include price elasticities from Labandeira et al. (2017) for the most carbon-intensive sectors into their model, and find that this does not change regressivity in a substantial way. Given that price elasticities for energy products are typically low (Labandeira et al., 2017), demand for these products decreases little after implementing the tax. The adjustment in consumption bundles in Feindt et al.'s model occurs uniformly across households, as elasticities are considered to be equal across household groups.

Dorband et al. (2019) discuss potential distributional implications of income-group specific price elasticities. They argue that carbon tax impacts could be more progressive since price-elasticities for food in low-income countries tend to be larger than in high-income countries (Muhammad et al., 2011 referenced in Dorband et al. 2019). Consequently, low-income households might react more to carbon pricing than high-income households, at least in low- and middle-income countries. In the high-income country context of the EU, these dynamics may be very different. If there is any variation of price elasticity across income groups, we hypothesise that counterfactual scenario results could in general be more regressive compared to static results, given that low-income households could be more affected by technological lock-in situations than high-income households, who have a higher ability to move, change transportation means, replace heating systems, etc. For the time being, we follow the review by Feindt el al. (2021) who refer to recent research suggesting that price elasticities do not vary significantly across household groups (Díaz & Medlock, 2021).

A second limitation of our research relates to uncertainties surrounding our underlying data and methodological uncertainties. First, data are subject to continuous review and improvement. Concordances between UNFCCC GHG accounting categories, UN ISIC economic sectors, and UN COICOP expenditure accounting categories cannot be created in a single way and matching processes can therefore induce measurement errors. The balancing process in the creation of global input-output time series provides an additional source of uncertainty. We also point out a methodological uncertainty in structural decomposition analysis, namely the assumption of factor independence. This assumption is most certainly violated, not least because the calculation of the Leontief matrix involves the inverse of total output, which is also used to calculate emissions intensities. We are not aware of any treatment of this problem in the decomposition literature, and we leave the creation of a structural decomposition formalisation in the presence of factor interdependence as an opportunity for future research.

6 Conclusion

Carbon pricing policies have thus far been implemented on specific fuels and industries, with substantial shares of emissions exempted. The implication is that different economic sectors have been subject to different average carbon prices, both within countries, across countries, and across time. The interconnections of value chains across economic sectors and countries imply that end product prices paid by consumers are affected by upstream carbon pricing policies in all countries. The goal of this paper is to evaluate the incidence of this carbon price heterogeneity around the world for households in the EU, and the potential distributional impacts of more comprehensive carbon pricing policies.

We match the World Carbon Pricing Database (WCPD) with the Global Resource Input Output Assessment (GLORIA) model, and disaggregate household demand vectors into household groups using European Household Budget Survey Data (Eurostat HBS). The resulting framework is a global social accounting matrix time series with both environmental, social, and policy accounts. We use this framework to run static complete incidence computations, taking account of the entirety of direct and indirect carbon pricing effects. Next to the use of this novel dataset, another contribution of our research is the application of temporal structural decomposition analysis (SDA) based on LMDI formulation for household-group specific carbon pricing incidence.

Our findings suggest that overall carbon pricing incidence on EU households has been smaller than previously estimated, as prices have not been implemented uniformly across economic sectors. The proportion of household expenditures spent on carbon varied between 0.2% and 1.4% in 2020. Importantly, we also find that impacts in most EU countries have been regressive, i.e., affecting low-income households more than their high-income counterparts. While earlier studies attributed this regressivity mainly to carbon intensities of consumption, we find that non-uniform carbon prices have been a further factor increasing regressivity: The higher carbon pricing burden on low-income households does not only reflect their larger spending shares on carbon-intensive products like heating, but also the fact that higher-income households consume disproportionately products subject to lower embodied carbon prices—not least imported ones. Carbon prices are the main factor of incidence and regressivity change over time, while carbon-reducing technological improvements, technical changes in the global economy, and changes in consumption bundles have not changed incidence substantially.

For most countries in the EU, we find that a uniform carbon price generating the same national fiscal revenues as the observed heterogenous baseline would be slightly less regressive across households. The least regressive impacts, on average, are observed with a uniform carbon price around the world, partly because it raises carbon prices embedded in EU imports. An alternative, more plausible scheme would be the IMF's Carbon Price Floor proposal, which would impose different prices for low-, middle- and high-income countries. In our framework, this scenario provides the second least regressive outcome. Our findings also imply that the ongoing extension of EU ETS coverage and the implementation of the EU's CBAM are likely to reduce the regressivity of carbon pricing in the EU, all else equal.

Bibliography

Abrell, J., Rausch, S., & Schwarz, G. A. (2018). How robust is the uniform emissions pricing rule to social equity concerns? *Journal of Environmental Economics and Management*, *92*, 783–814. https://doi.org/10.1016/J.JEEM.2017.09.008

Akoğuz, C. E., Capéau, B., Decoster, A., De Sadeleer, L., Güner, D., Manios, K., … Vanheukelom, T. (2020). *A new indirect tax tool for EUROMOD Final Report*. Retrieved from https://euromod-web.jrc.ec.europa.eu/sites/default/files/2021-03/A new indirect tax tool for EUROMOD Final Report.pdf

Amores, A. F., Maier, S., & Ricci, M. (2022). *Taxing Households Energy Consumption in the EU: the Tax Burden and its Redistributive effect* (No. 06/2022, JRC Working Papers on Taxation and Structural Reforms). Retrieved from https://joint-research-centre.ec.europa.eu/system/files/2022-09/JRC130358_wp06-22_final.pdf

Andersson, J., & Atkinson, G. (2020). *The distributional effects of a carbon tax: The role of income inequality* (No. 378, Centre for Climate Change Economics and Policy Working Paper; No. 349, Grantham Research Institute on Climate Change and the Environment Working Paper). Retrieved from https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2020/09/working-paper-349-Andersson-Atkinson.pdf

Ang, B. W., & Choi, K.-H. (1997). Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method. *The Energy Journal*, *18*(3), 59–73. Retrieved from https://www.jstor.org/stable/41322738

Ang, B. W., & Liu, F. L. (2001). A new energy decomposition method: perfect in decomposition and consistent in aggregation. *Energy*, *26*(6), 537–548. Retrieved from https://doi.org/10.1016/S0360-5442(01)00022-6

Antosiewicz, M., Fuentes, J. R., Lewandowski, P., & Witajewski-Baltvilks, J. (2022). Distributional effects of emission pricing in a carbon intensive economy: The case of Poland. *Energy Policy*, *160*(112678). https://doi.org/10.1016/j.enpol.2021.112678

Böhringer, C., Rutherford, T. F., & Schneider, J. (2021). The incidence of CO2 emissions pricing under alternative international market responses. *Energy Economics*, *101*(105404). https://doi.org/10.1016/j.eneco.2021.105404

Boyce, J. K. (2018). Carbon Pricing: Effectiveness and Equity. *Ecological Economics*, *150*, 52–61. https://doi.org/10.1016/J.ECOLECON.2018.03.030

Bruvoll, A. (2013). The Misinterpretation of Pigouvian Taxes. *Journal of Environmental Protection*, *4*, 154–160. https://doi.org/10.4236/jep.2013.48A1017

Chancel, L. (2022). Global carbon inequality over 1990–2019. *Nature Sustainability*, *5*(11), 931–938. https://doi.org/10.1038/s41893-022-00955-z

CPLC. (2017). *Report of the High-Level Commission on carbon Prices*. Retrieved from https://www.carbonpricingleadership.org/report-of-the-highlevel-commission-on-carbon-prices

Cullenward, D., & Victor, D. G. (2020). *Making Climate Policy Work*. Retrieved from https://www.perlego.com/book/1978801/making-climate-policy-work-pdf

De Boer, P. (2008). Additive Structural Decomposition Analysis and Index Number Theory: An Empirical Application of the Montgomery Decomposition. *Economic Systems Research*, *20*(1). https://doi.org/10.1080/09535310801892066 de Boer, P., & Rodrigues, J. F. D. (2020). Decomposition analysis: when to use which method? *Economic Systems Research*, *32*(1), 1–28. https://doi.org/10.1080/09535314.2019.1652571

Díaz, A. O., & Medlock, K. B. (2021). Price elasticity of demand for fuels by income level in Mexican households. *Energy Policy*, *151*, 112132. https://doi.org/10.1016/J.ENPOL.2021.112132

Dolphin, G., & Merkle, M. (n.d.). Emissions-weighted carbon price: Sources and Methods. *Scientific Data*, *forthcomin*(previous version available from RFF). Retrieved from https://www.rff.org/publications/working-papers/emissions-weighted-carbon-price-sources-and-methods/

Dolphin, G., Pollitt, M. G., & Newbery, D. M. (2020). The political economy of carbon pricing: a panel analysis. *Oxford Economic Papers*, *72*(2). https://doi.org/10.1093/oep/gpz042

Dolphin, G., & Xiahou, Q. (2022). World carbon pricing database: sources and methods. *Scientific Data 2022 9:1*, *9*(1), 1–7. https://doi.org/10.1038/s41597-022-01659-x

Dorband, I. I., Jakob, M., Kalkuhl, M., & Steckel, J. C. (2019). Poverty and distributional effects of carbon pricing in low- and middle-income countries – A global comparative analysis. *World Development*, *115*, 246–257. https://doi.org/10.1016/J.WORLDDEV.2018.11.015

Douenne, T., & Fabre, A. (2022). Yellow Vests, Pessimistic Beliefs, and Carbon Tax Aversion. *AMERICAN ECONOMIC JOURNAL: ECONOMIC POLICY*, *14*(1), 81–110. https://doi.org/10.1257/pol.20200092

Emonts-Holley, T., Ross, A., & Swales, K. (2021). Estimating induced effects in IO impact analysis: variation in the methods for calculating the Type II Leontief multipliers. *Economic Systems Research*, *33*(4). https://doi.org/10.1080/09535314.2020.1837741

European Commission. (2023a). Carbon Border Adjustment Mechanism. Retrieved from https://taxation-customs.ec.europa.eu/carbon-border-adjustment-mechanism_en

European Commission. (2023b). Development of EU ETS (2005-2020). Retrieved from https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/development-eu-ets-2005-2020_en#phase-3-2013-2020

European Commission. (2023c). ETS 2: buildings, road transport and additional sectors. Retrieved from https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/ets-2-buildings-road-transport-and-additional-sectors_en

Eurostat. (2023). Household Budget Surveys (HBS) - Overview. Retrieved from https://ec.europa.eu/eurostat/web/household-budget-surveys

Feindt, S., Kornek, U., Labeaga, J. M., Sterner, T., & Ward, H. (2021). Understanding regressivity: Challenges and opportunities of European carbon pricing. *Energy Economics*, *103*, 105550. https://doi.org/10.1016/J.ENECO.2021.105550

Finch, A., & van den Bergh, J. (2022). Assessing the authenticity of national carbon prices: A comparison of 31 countries. *Global Environmental Change*, *74*(102525). https://doi.org/10.1016/j.gloenvcha.2022.102525

Fremstad, A., & Paul, M. (2019). The Impact of a Carbon Tax on Inequality. *Ecological Economics*, *163*, 88–97. https://doi.org/10.1016/J.ECOLECON.2019.04.016

Fullerton, D., & Muehlegger, E. (2019). Who Bears the Economic Burdens of Environmental Regulations? *Review of Environmental Economics and Policy*, *13*(1), 62–82. https://doi.org/10.1093/REEP/REY023

Goulder, L. H., Hafstead, M. A. C., Kim, G., & Long, X. (2019). Impacts of a carbon tax across US household income groups: What are the equity-efficiency trade-offs? *Journal of Public Economics*, *175*, 44–64. https://doi.org/10.1016/j.jpubeco.2019.04.002

Hänsel, M. C., Franks, M., Kalkuhl, M., & Edenhofer, O. (2022). Optimal carbon taxation and horizontal equity: A welfare-theoretic approach with application to German household data. *Journal of Environmental Economics and Management*, *116*, 102730. https://doi.org/10.1016/j.jeem.2022.102730

Hoekstra, R., & van den Bergh, J. (2003). Comparing structural and index decomposition analysis. *Energy Economics*, *25*(1), 39–64. https://doi.org/10.1016/S0140-9883(02)00059-2

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., … Houser, T. (2017). Estimating economic damage from climate change in the United States. *Science*, *356*(6345), 1362–1369. https://doi.org/10.1126/SCIENCE.AAL4369

Ivanova, D., & Wood, R. (2020). The unequal distribution of household carbon footprints in Europe and its link to sustainability. *Global Sustainability*, *3*, e18. https://doi.org/10.1017/SUS.2020.12

Labandeira, X., Labeaga, J. M., & López-Otero, X. (2017). A meta-analysis on the price elasticity of energy demand. *Energy Policy*, *102*, 549–568. https://doi.org/10.1016/J.ENPOL.2017.01.002

Lenzen, M., Geschke, A., Abd Rahman, M. D., Xiao, Y., Fry, J., Reyes, R., … Yamano, N. (2017). The Global MRIO Lab - charting the world economy. *Econonomic Systems Research*, *29*(2), 158–186. https://doi.org/10.1080/09535314.2017.1301887

Lenzen, M., Geschke, A., West, J., Fry, J., Malik, A., Giljum, S., … Schandl, H. (2021). Implementing the material footprint to measure progress towards Sustainable Development Goals 8 and 12. *Nature Sustainability*, *5*, 147–166. https://doi.org/10.1038/s41893-021-00811-6

Maestre-Andrés, S., Drews, S., & van den Bergh, J. (2019). Perceived fairness and public acceptability of carbon pricing: a review of the literature. *Climate Policy*, *19*(9), 1186–1204. https://doi.org/10.1080/14693062.2019.1639490

Mayer, J., Dugan, A., Bachner, G., & Steininger, K. W. (2021). Is carbon pricing regressive? Insights from a recursive-dynamic CGE analysis with heterogeneous households for Austria. *Energy Economics*, *104*(105661). https://doi.org/10.1016/j.eneco.2021.105661

Missbach, L., Steckel, J. C., & Vogt-Schilb, A. (2022). *Cash transfers in the context of carbon pricing reforms in Latin America and the Caribbean* (No. 01404, IDB Working Paper Series). Retrieved from https://www.efdinitiative.org/publications/cash-transfers-context-carbon-pricing-reforms-latin-america-and-caribbean

Muhammad, A., Seale, J. L., Meade, B., & Regmi, A. (2011). *International evidence on food consumption patterns: An update using 2005 international comparison program data*. Retrieved from U.S. Department of Agriculture, Economic Research Service website: https://www.ers.usda.gov/webdocs/publications/47579/7637_tb1929.pdf?v=6325.7

Neuhoff, K., & Ritz, R. A. (2019). *Carbon cost pass-through in industrial sectors* (No. 1935, EPRG Working Paper; No. 1988, Cambridge Working Paper in Economics). Retrieved from https://www.jstor.org/stable/resrep30282?seq=1

Ohlendorf, N., Jacob, M., Minx, J. C., Schröder, C., & Steckel, J. C. (2021). Distributional Impacts of Carbon Pricing: A Meta-Analysis. *Environmental and Resource Economics*, *78*, 1–42.

Olson, M. (1965). *The logic of collective action. Public Goods and the Theory of Groups*. Cambridge, Massachusets: Harvard University Press.

Peñasco, C., Díaz Anadón, L., & Verdolini, E. (2021). Systematic review of the outcomes and trade-offs of ten types of decarbonization policy instruments. *Nature Climate Change*, *11*, 257–265. https://doi.org/10.1038/s41558-020-00971-x

Pigou, A. C. (1920). *The Economics of Welfare*. London: Macmillan.

Rafaty, R., Dolphin, G., & Pretis, F. (2021). *Carbon pricing and the elasticity of CO2 emissions* (No. 21–33, RFF Working Paper). Retrieved from https://www.rff.org/publications/working-papers/carbon-pricing-and-the-elasticity-of-co2-emissions/

Rausch, S., Metcalf, G. E., & Reilly, J. M. (2011). Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics*, *33*, S20–S33. https://doi.org/10.1016/j.eneco.2011.07.023

Rennert, K., Errickson, F., Prest, B. C., Rennels, L., Newell, R. G., Pizer, W., … Anthoff, D. (2022). Comprehensive evidence implies a higher social cost of CO2. *Nature*, *610*, 687–692. https://doi.org/10.1038/s41586-022-05224-9

Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., … Séférian, R. (2018). Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. In V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, … T. Waterfield (Eds.), *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,* (pp. 93–174). https://doi.org/10.1017/9781009157940.004

Rose, A., & Casler, S. (1996). Input-Output Structural Decomposition Analysis: A Critical Appraisal. *Economic Systems Research*, *8*(1). https://doi.org/10.1080/09535319600000003

Sager, L. (2021). *The Global Consumer Incidence of Carbon Pricing: Evidence from Trade* (No. 352, Centre for Climate Change Economics and Policy Working Paper; No. 320, Grantham Research Institute on Climate Change and the Environment Working Paper). Retrieved from https://www.lse.ac.uk/GranthamInstitute/wp-content/uploads/2019/04/working-paper-320-Sager.pdf

Stigler, G. J. (1971). The Theory of Economic Regulation. *The Bell Journal of Economics and Management Science*, *2*(1), 3–21. https://doi.org/10.2307/3003160

Su, B., & Ang, B. W. (2012). Structural decomposition analysis applied to energy and emissions: Some methodological developments. *Energy Economics*, *34*(1), 177–188. https://doi.org/10.1016/J.ENECO.2011.10.009

Suits, D. (1977). Measurement of Tax Progressivity. *The American Economic Review*, *67*(747–752). Retrieved from https://www.jstor.org/stable/1813408

Tavoni, A., & Winkler, R. (2021). Domestic Pressure and International Climate Cooperation. *Annual Review of Resource Economics*, *13*, 225–243. https://doi.org/10.1146/annurev-resource-101420-105854

Timilsina, G. R. (2022). Carbon Taxes. *Journal of Econonomic Literature*, *60*(4), 1456–1502. https://doi.org/10.1257/jel.20211560

Trading Economics. (2023). EU Carbon Permits. Retrieved from https://tradingeconomics.com/commodity/carbon

U.S. EPA. (2023). *Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances*. Retrieved from https://www.epa.gov/system/files/documents/2023-

12/epa_scghg_2023_report_final.pdf

Wachsmann, U., Wood, R., Lenzen, M., & Schaeffer, R. (2009). Structural decomposition of energy use in Brazil from 1970 to 1996. *Applied Energy*, *86*, 578–587. https://doi.org/10.1016/j.apenergy.2008.08.003

Wood, R., & Lenzen, M. (2006). Zero-value problems of the logarithmic mean divisia index decomposition method. *Energy Policy*, *43*(12), 1326–1331. https://doi.org/10.1016/j.enpol.2004.11.010

World Bank Group. (2023). *State and Trends of Carbon Pricing 2023*. Retrieved from https://openknowledge.worldbank.org/bitstreams/bdd449bb-c298-4eb7-a794-c80bfe209f4a/download

Appendix A: Matching WCPD and GLORIA

Procedure Description

The world carbon pricing dataset (WCPD) (Dolphin, 2023a, 2023b) provides carbon prices by emission category, following the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Detailed reports explaining the accounting framework are available online (IPCC, 2023). The structure of the IPCC emission categories is summarised in figure FA1.1 below. WCPD provides data at up to 5-digit IPCC category code. The total number of categories for each year and country is 77.

Economic structure data is commonly provided at economic sector classification, following for example the International Standard Industrial Classification (ISIC), or the European Nomenclature of Economic Activities (NACE). The industrial classification used in the Global Resource Input-Output Assessment model (GLORIA) (Industrial Ecology Lab, 2023) is based on ISIC rev.4, and provided at 120 sector resolution for each year and country. We aggregate sectors to 60 for each country, and aggregate countries to 54 regions, reflecting the needs for our analysis and data availability from Eurostat. Table TA1 below lists all resulting sectors. Greenhouse-gas emission satellite data is provided for each sector in a disaggregated format, consistent with the EU Emissions Database for Global Atmospheric Research (EDGAR) (European Commission, 2023). The disaggregation follows the IPCC 2006 classification, and therefore enables us to use a precise mapping process for imputing emissions-weighted carbon prices at the GLORIA sector resolution.

For our analysis, we match WCPD data to GLORIA sectors using a process-based algorithm. GLORIA CO_2 emission satellites are provided in 73 IPCC categories per country-sector, therefore the first step is an aggregation of the WCPD data from 77 to 73 categories. Where low level subcategories map onto higher level categories, we impose an emissions-weighted average carbon price. As a second step, we multiply for each sector and country the categorical emissions with the categorical carbon prices and divide by total emissions. The result is a country-sector specific emission-weighted carbon price.

Code

Matching scripts are available on the project repository, subdirectory datamatch/2_ecp_gloria (https://github.com/jmmnmbu/ecp_distrib/tree/main/datamatch/2_ecp_gloria). Access available upon request.

Checkplots

All post-matching price plots, cross sectoral and cross country, can be viewed in the project repository, subdirectory descr_hl3/price_var. Access available upon request. We add panel plots for the year 2020 at the end of this appendix section.

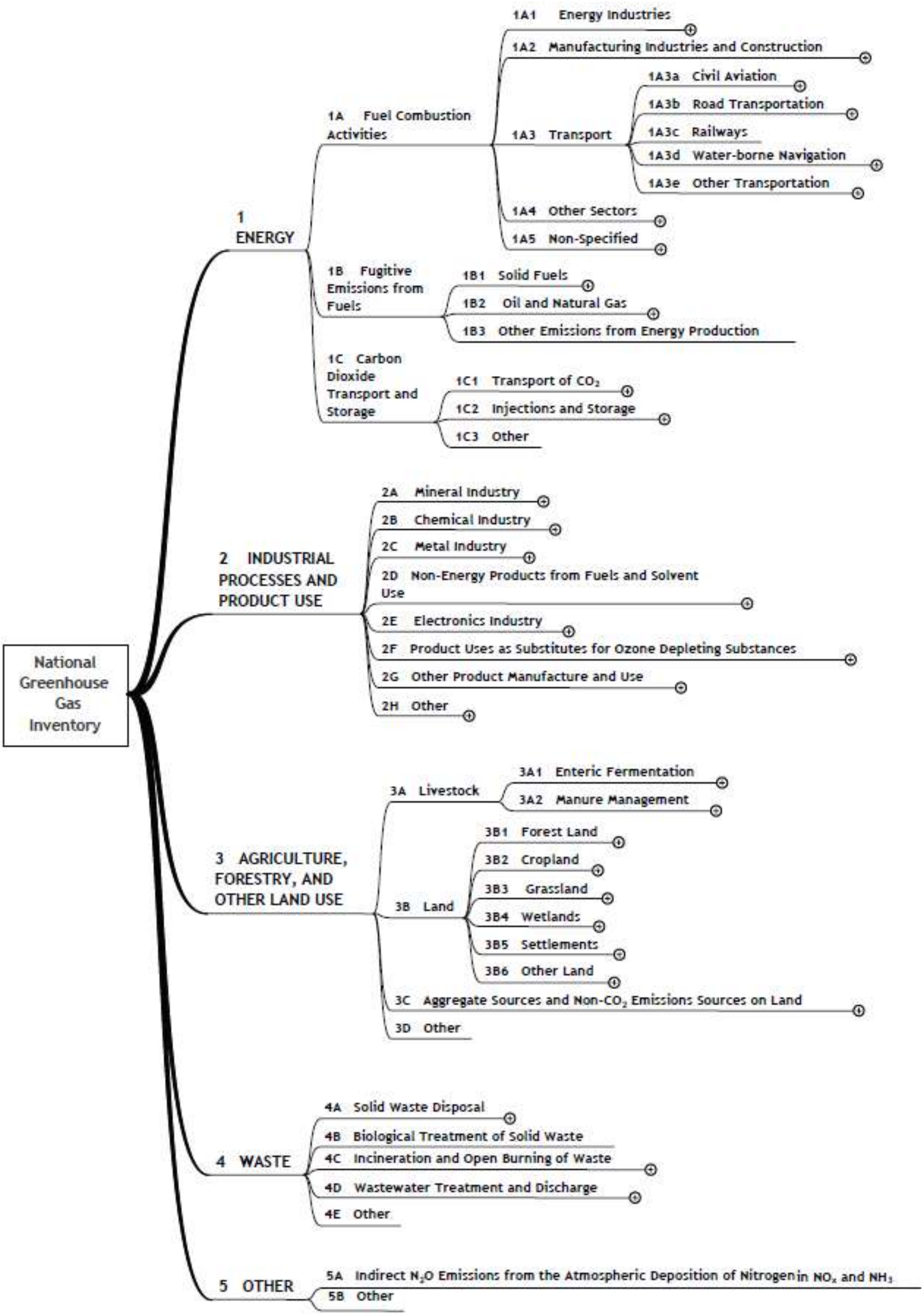

Figure FA.A.1: IPCC 2006 Greenhouse Gas Inventory framework (IPCC 2023, p.6)

Table TAA1: GLORIA Sectors Aggregated

No.	*Sector*	*No.*	*Sector*
1	*Agriculture*	*31*	*Machinery and equipment*
2	*Forestry*	*32*	*Motor vehicles & transport equip*
3	*Fishing*	*33*	*Repair and installation of machinery*
4	*Coal extraction*	*34*	*Computers, electronics & optical*
5	*Petroleum extraction*	*35*	*Electrical equipment*
6	*Gas extraction*	*36*	*Furniture & other manuf*
7	*Other mining & quarrying*	*37*	*Electric power*
8	*Meat*	*38*	*Gas supply*
9	*Fish*	*39*	*Water & sewage*
10	*Cereals*	*40*	*Waste & recycling*
11	*Veg*	*41*	*Construction*
12	*Fruit*	*42*	*Wholesale and retail trade; repair of motor vehicles and motorcycles*
13	*Other food*	*43*	*Road transport*
14	*Dairy*	*44*	*Rail transport*
15	*Beverage*	*45*	*Pipeline transport*
16	*Tobacco*	*46*	*Water transport*
17	*Textiles & leather*	*47*	*Air transport*
18	*Sawmill, pulp, paper*	*48*	*Services to transport*
19	*Printing*	*49*	*Postal & courier*
20	*Coke oven products*	*50*	*Hospitality*
21	*Refined petroleum products*	*51*	*Publishing*
22	*Fertilizers*	*52*	*Telecomm*
23	*Other chemicals*	*53*	*IT*
24	*Pharma*	*54*	*Finance & Insurance*
25	*Paint, glues, detergents, other*	*55*	*Property and real estate*
26	*Rubber & plastic*	*56*	*Government; social security; defence; public order*
27	*Cement, lime and plaster products*	*57*	*Education*
28	*Other non-metallic minerals*	*58*	*Human health and social work activities*
29	*Basic metals*	*59*	*Arts, entertainment and recreation*
30	*Fabricated metal products*	*60*	*Other services*

References

Dolphin (2023a). *World Carbon Pricing Database*. Available at: https://github.com/g-dolphin/WorldCarbonPricingDatabase (last accessed 20 April 2023)

Dolphin (2023b). *Emissions-weighted Carbon Price*. Available at: https://github.com/g-dolphin/ECP (last accessed 20 April 2023)

European Commission (2023). *EDGAR – Emissions Database for Global Atmospheric Research.* Available at: https://edgar.jrc.ec.europa.eu/ (last accessed 20 April 2023).

Industrial ecology virtual lab (2023). *GLORIA*. Available at: https://ielab.info/analyse/gloria (last accessed 20 April 2023)

IPCC (2023). *Task Force on National Greenhouse Gas Inventories. 2006 IPCC Guidelines for National Greenhouse Gas Inventories.* Available at: https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html (last accessed 20 April 2023).

Panel Plots 2020

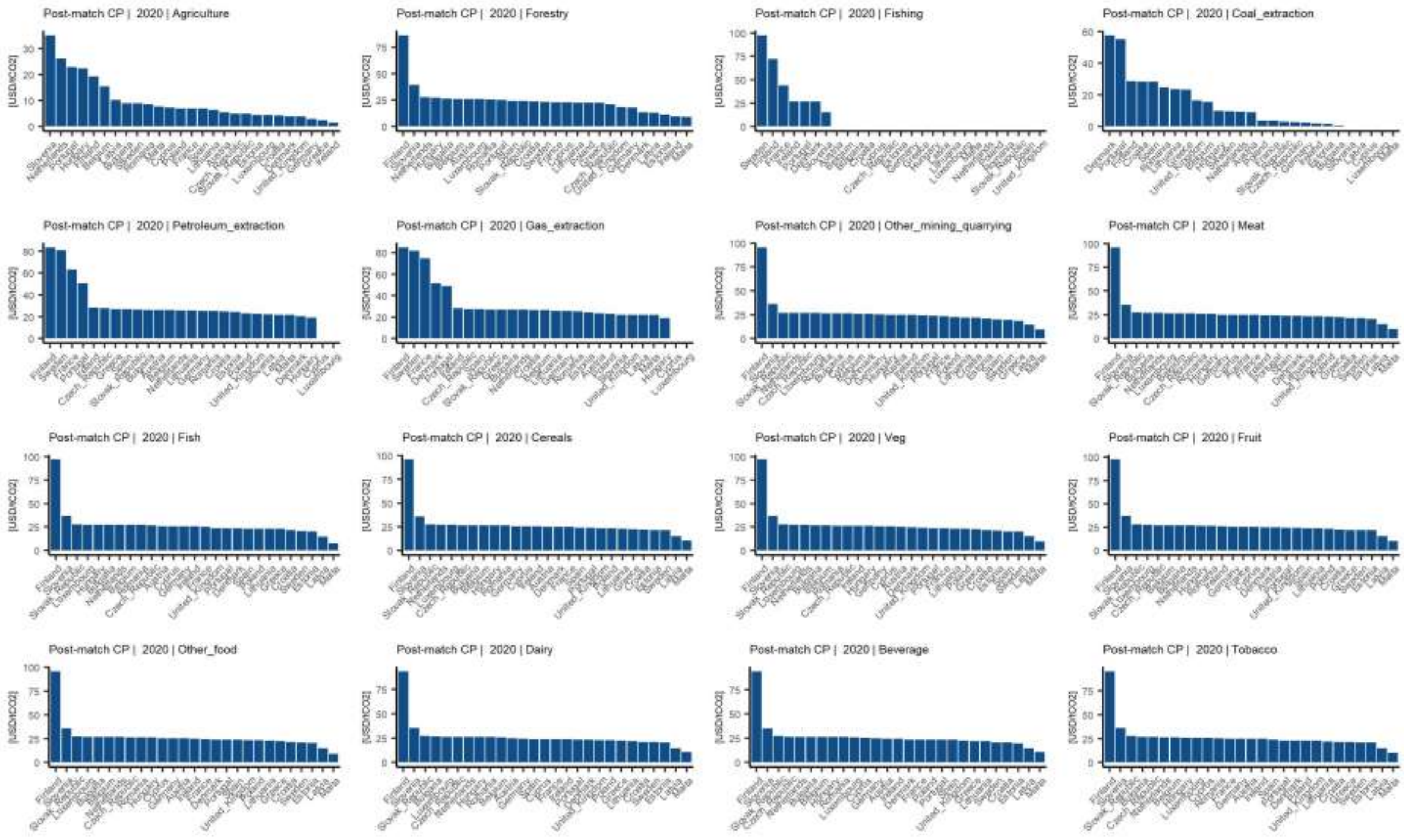

Figure FA.A.2: Post-matching emissions-weighted carbon price plots for sectors 1 to 16. Countries ordered according to price for each sector.

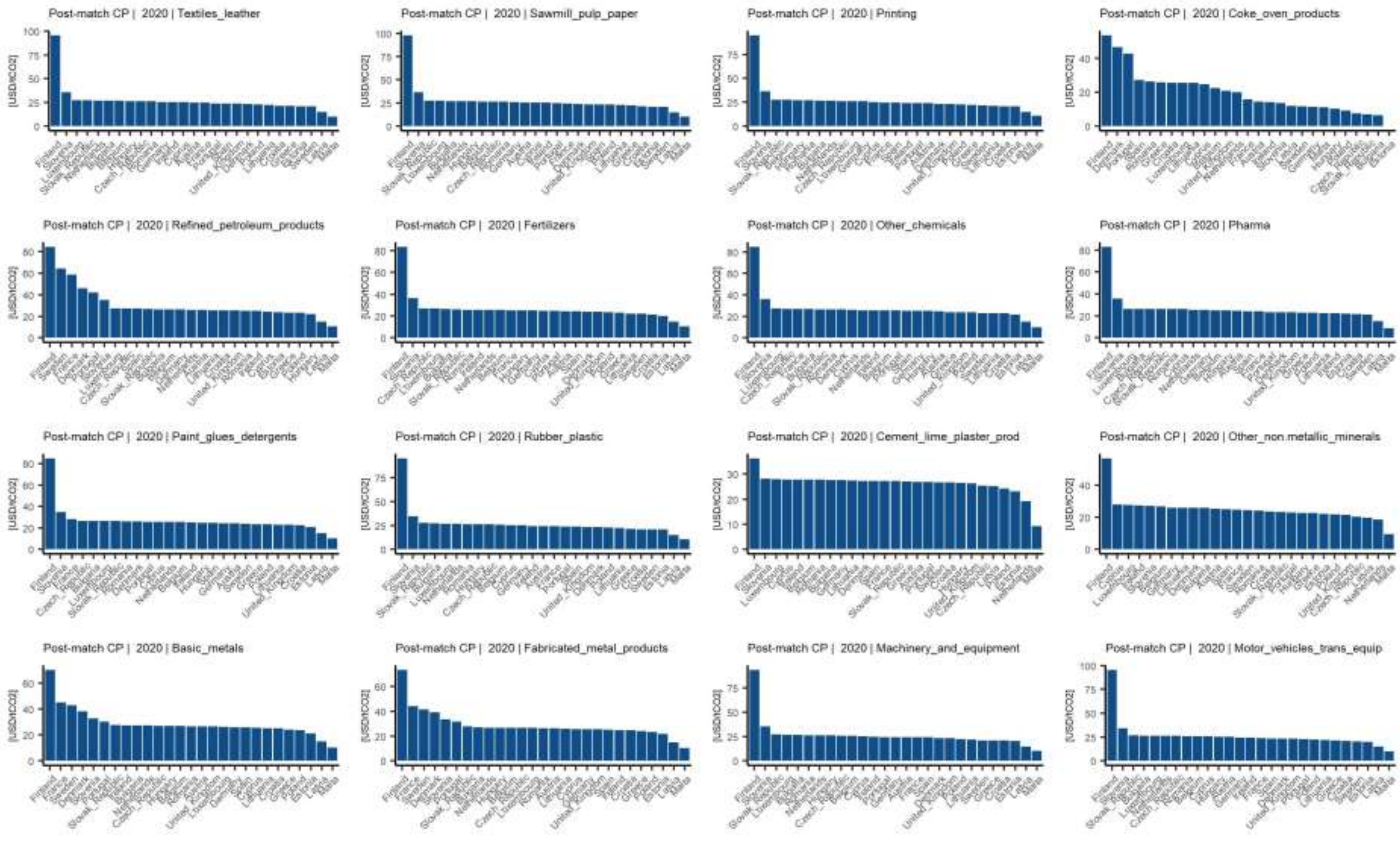

Figure FA.A.3: Post-matching emissions-weighted carbon price plots for sectors 17 to 32. Countries ordered according to price for each sector.

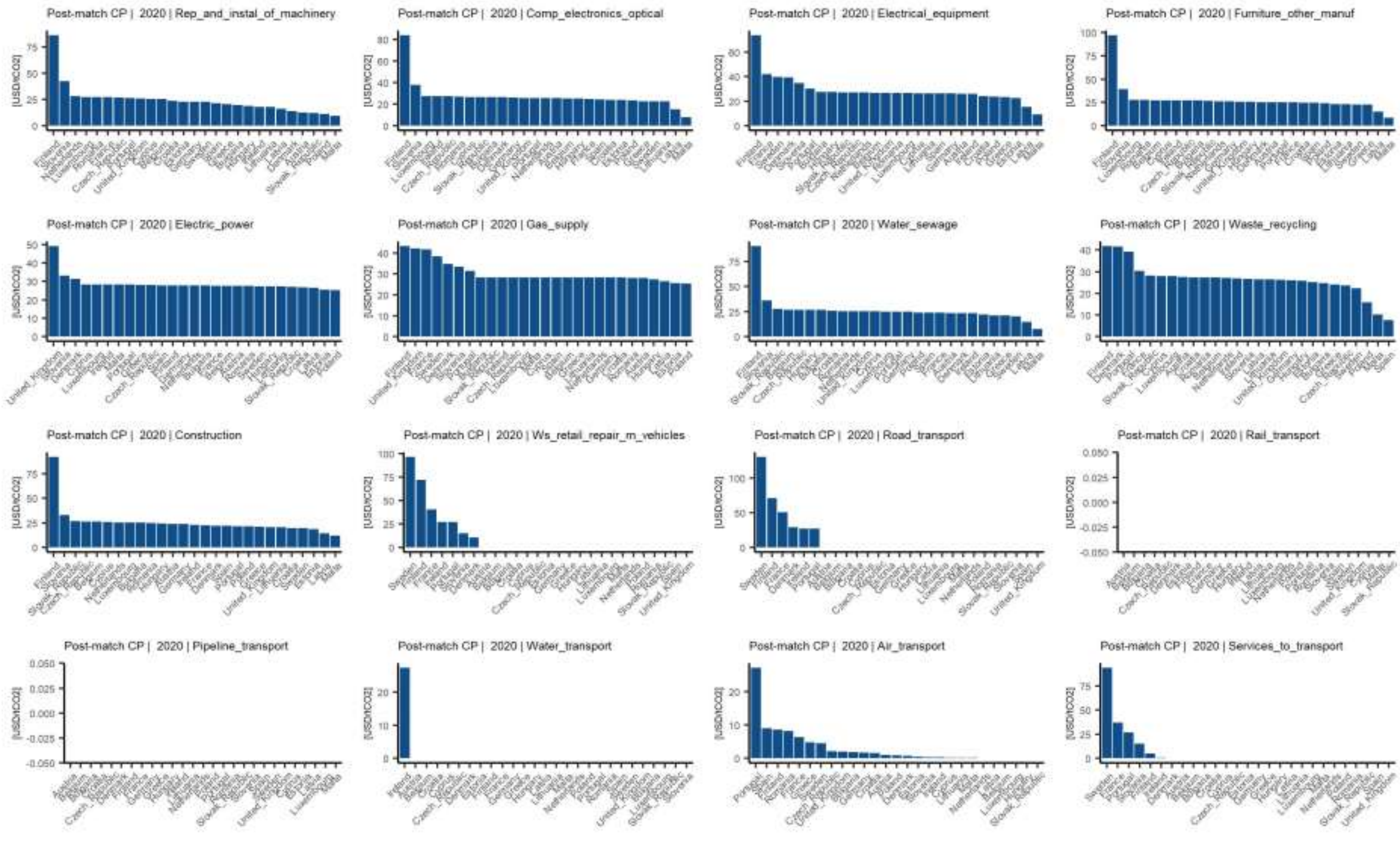

Figure FA.A.4: Post-matching emissions-weighted carbon price plots for sectors 33 to 48. Countries ordered according to price for each sector.

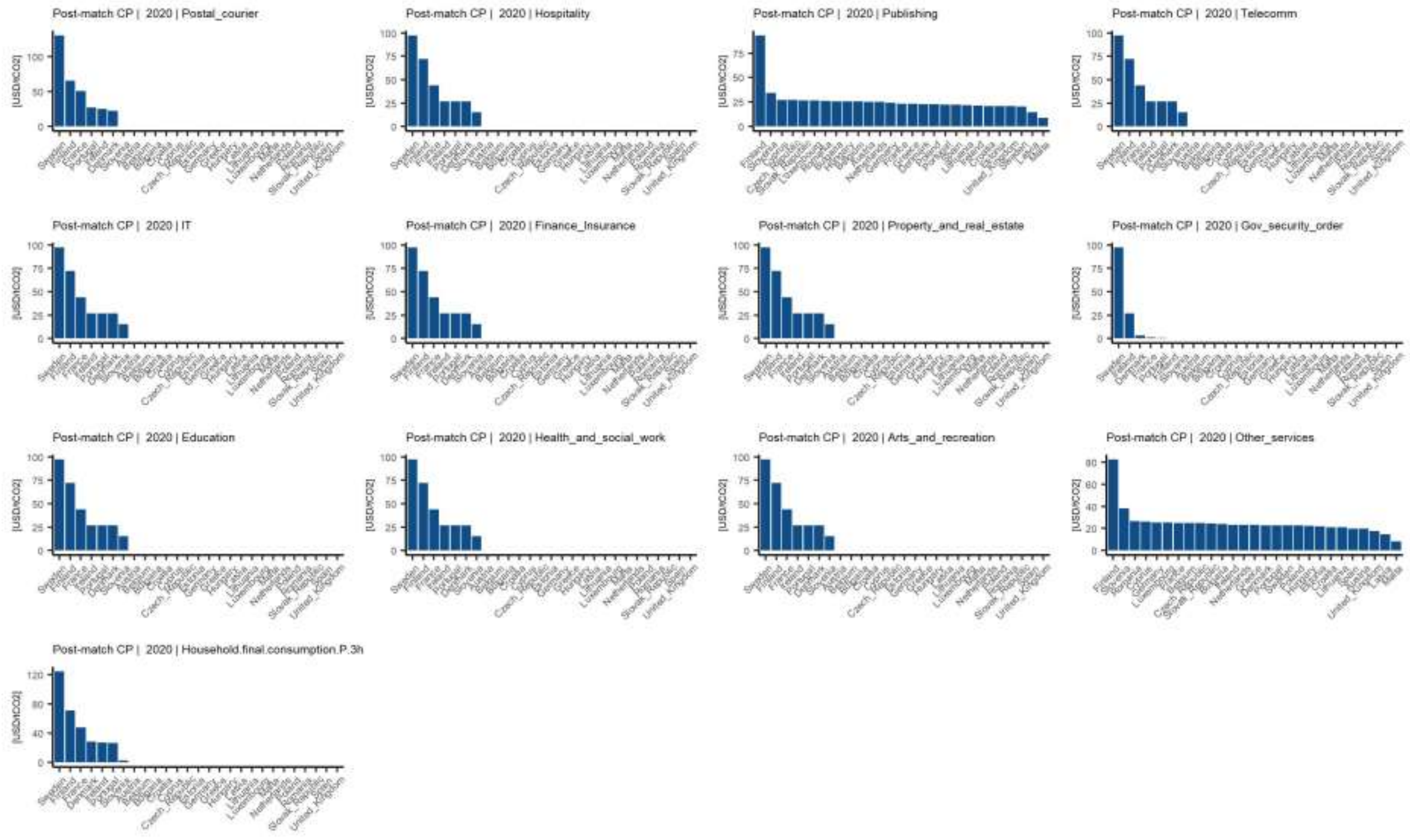

Figure FA.A.5: Post-matching emissions-weighted carbon price plots for sectors 49 to 61. Countries ordered according to price for each sector.

Appendix B: Matching HBS Data with GLORIA

Introduction

We use household expenditure data from the European Household Budget Survey (HBS) (Eurostat, 2023). This data is based on the UN Classification of Individual Consumption by Purpose (COICOP) – a framework made for analyses of household consumption statistics (UNSD, 2018). We use the scientific use level 3 (four digit) resolution data, which amounts to 112 consumption categories in total. Not all EU countries are provided in the HBS scientific use files, and some of those that are provided come with missing data.

The COICOP system of the household expenditure data does not correspond to the ISIC system of the GLORIA input-output data in a unique way. ISIC stands for International Standard Industrial Classification of All Economic Activities, and is commonly used for multi-sector economic analyses (UNSD, 2008). To map household expenditure data to our analytical framework, we use a process that maintains the relative differences in expenditure size and expenditure composition between household quantiles but rescales the data so that totals are consistent with the demand accounts of GLORIA. For sector-specific demands, the difference between consumer groups is assumed to be equal across product-origin. For example, if the second consumer quantile buys 1.5 times more apples than the first consumer quantile, then this relation applies to both domestically sourced apples as well as imported apples.

Our method provides a vector $\mathbf{r}$ of household quantile expenditure by GLORIA sectors. It requires as inputs:

- Total consumer demand by country across ISIC sectors denoted vector $\mathbf{r}$, where the number of elements is K
- Demand of a certain household income quantile by COICOP category, denoted vector $\mathbf{h}$, where the number of elements is I. The matrix including all household groups is denoted $\mathbf{H}$.
- The totals of all household income quantiles by COICOP category, denoted vector $\mathbf{t}$, with number of elements I.
- Concordance matrix $\mathbf{C}$ of dimension $\mathrm{K} \times \mathrm{I}$ with elements 0 and 1. Concordance defines whether a COICOP category and a GLORIA sector are associated or not. Element 0 means there is no concordance, element 1 means there is concordance.

The method consists of three main steps.

Step 1: Compute disaggregation keys for COICOP categories across GLORIA sectors

We start out by multiplying our concordance matrix $\mathbf{C}$ with total expenditure $\mathbf{t}$ and aggregating across columns by multiplying with a vector of ones $\mathbf{u}$.

$$\boldsymbol{v} = \boldsymbol{C} * diag(\boldsymbol{t}) * \boldsymbol{u} \qquad (A.B.1)$$

The resulting vector $\mathbf{v}$ is of dimension $\mathrm{K} \times 1$ and provides for each GLORIA sector k the sum of COICOP category totals that are associated with it. As a next step we take the inverse values of $\mathbf{v}$ and multiply them with our concordance table. In cases where elements are divided by zero, we impose the element result to be equal to 0. Then we multiply the result with our total expenditure vector.

$$\boldsymbol{W} = diag(\boldsymbol{v}^{-1}) * \boldsymbol{C} * diag(\boldsymbol{t}) \qquad (A.B.2)$$

The resulting matrix $\mathbf{W}$ has the same dimension as the concordance matrix. Elements of $\mathbf{W}$ can assume three different kinds of values. They are:

- equal to zero at each element where concordance is zero,
- equal to one at each element where only a single COICOP category maps onto the GLORIA sector,
- equal to a fraction between zero and one where several COICOP categories map onto the GLORIA sector. This fraction is equal to the proportion of the COICOP category relative to all COICOP categories that are associated with the respective GLORIA sector.

Step 2: Compute scaling keys to account for heterogenous household groups

Next we include our household group specific data into the calculation. Note that the individual household quantile expenditure $\mathbf{h}$ constitutes a part of $\mathbf{t}$:

$$\boldsymbol{t} = \boldsymbol{H} * \boldsymbol{u} \qquad (A.B.3)$$

We multiply the inverse elements of total expenditure $\mathbf{t}$ with the household quantile expenditure $\mathbf{h}$. Again, in cases where elements are divided by zero, we impose the element result to be equal to 0.

$$\boldsymbol{M} = \boldsymbol{C} * diag[diag(\boldsymbol{t}^{-1}) * \boldsymbol{h}] \qquad (A.B.4)$$

The term in square brackets provides a vector of dimension $\mathrm{I} \times 1$, essentially giving us the proportion of total expenditure for a COICOP class that is spent by the household group in question. Diagonalising this vector and post-multiplying it with our concordance matrix provides us with matrix $\mathbf{M}$, which gives us household group expenditure proportion for each element where concordance is equal to one.

Step 3: Compute rescaled demand of a household group fitted to GLORIA

In order to create a weighting vector to yield our desired result, we now compute the Hadamard product of our matrices $\mathbf{M}$ and $\mathbf{W}$ and sum across columns.

$$\boldsymbol{q} = [\boldsymbol{M} \circ \boldsymbol{W}] * \boldsymbol{u} \qquad (A.B.5)$$

The resulting vector $\mathbf{q}$ is again $\mathrm{K} \times 1$ and gives us the fractions of final demand for which the household group in question is accountable. This vector can be applied to all GLORIA sectors that are associated with at least one COICOP category. One challenge is that not all GLORIA sectors can be connected to the household consumption classification system. Basic metals, for example, is a primary manufacturing sector that does not relate any COICOP category because consumers tend to consume fabricated products rather than raw materials. In most cases the final demand for these sectors in GLORIA is small, as their output is mainly used as inputs to downstream sectors. It does occur, however, that consumer demand for such sector outputs is non-zero in GLORIA. Where that is the case, we need to allocate this demand across household groups, without having any sector-specific distribution key available from the COICOP data. To minimise subjectivity, we choose a key that reflects total expenditure difference between household groups.

$$\frac{h_1 + h_2 + h_3}{t_1 + t_2 + t_3} = \frac{u^T * h}{u^T * t} = \frac{h_{total}}{t_{total}} \qquad (A.B.6)$$

The final vector to identify parts of $\mathbf{f}$ that can be attributed to the household group in question is then given by $\mathbf{b}$, which is in most cases equal to $\mathbf{q}$, and in zero-concordance cases it is equal to $\frac{h_{total}}{t_{total}}$.

$$\boldsymbol{b} = \begin{cases} \frac{h_{total}}{t_{total}} & for\ vector\ elements\ where\ v = 0 \\ q & otherwise \end{cases} \qquad (A.B.7)$$

To obtain absolute demand values for the household group across all GLORIA sectors we multiply the fractions given by $\mathbf{b}$ with our GLORIA demand vector $\mathbf{f}$.

$$\boldsymbol{r} = diag(\boldsymbol{b}) * \boldsymbol{f} \qquad (A.B.8)$$

Vector $\mathbf{r}$ is of the same dimension of $\mathbf{f}$ and constitutes the part of $\mathbf{f}$ that is consumed by the household quantile in question. All individual $\mathbf{r}$ add up to total GLORIA demand, that is:

$$\boldsymbol{f} = \boldsymbol{R} * \boldsymbol{u} \qquad (A.B.9)$$

Example

Consider the following example where we assume a simple case of three GLORIA sectors and three COICOP categories.

$$\boldsymbol{C} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}; \boldsymbol{t} = \begin{pmatrix} t_1 \\ t_2 \\ t_3 \end{pmatrix} \qquad (A.B.10)$$

<u>Step 1</u>

Vector $\mathbf{v}$ would then be:

$$\boldsymbol{v} = \begin{pmatrix} 0 \\ t_3 \\ t_1 + t_2 \end{pmatrix} \qquad (A.B.11)$$

Our matrix $\mathbf{W}$ would then be:

$$\boldsymbol{W} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & \frac{t_3}{t_3} \\ \frac{t_1}{t_1 + t_2} & \frac{t_2}{t_1 + t_2} & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ \frac{t_1}{t_1 + t_2} & \frac{t_2}{t_1 + t_2} & 0 \end{pmatrix} \qquad (A.B.12)$$

<u>Step 2</u>

Assuming a vector of household group specific expenditure:

$$\boldsymbol{h} = \begin{pmatrix} h_1 \\ h_2 \\ h_3 \end{pmatrix} \qquad (A.B.13)$$

Our matrix $\mathbf{M}$ would be:

$$\boldsymbol{M} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & \frac{h_3}{t_3} \\ \frac{h_1}{t_1} & \frac{h_2}{t_2} & 0 \end{pmatrix} \qquad (A.B.14)$$

Step 3

Assume our GLORIA demand to be given by:

$$\boldsymbol{f} = \begin{pmatrix} f_1 \\ f_2 \\ f_3 \end{pmatrix} \qquad (A.B.15)$$

First, we compute the Hadamard product:

$$\boldsymbol{M} \circ \boldsymbol{W} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & \frac{h_3}{t_3} \\ \frac{h_1}{t_1} & \frac{h_2}{t_2} & 0 \end{pmatrix} \circ \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ \frac{t_1}{t_1 + t_2} & \frac{t_2}{t_1 + t_2} & 0 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & \frac{h_3}{t_3} \\ \frac{h_1}{t_1 + t_2} & \frac{h_2}{t_1 + t_2} & 0 \end{pmatrix} \qquad (A.B.16)$$

Summing across columns gives us the weighting vector:

$$\boldsymbol{q} = \begin{pmatrix} 0 \\ \frac{h_3}{t_3} \\ \frac{h_1 + h_2}{t_1 + t_2} \end{pmatrix} \qquad (A.B.17)$$

Adding our process for zero-concordance cases:

$$\boldsymbol{b} = \begin{pmatrix} \frac{h_{total}}{t_{total}} \\ \frac{h_3}{t_3} \\ \frac{h_1 + h_2}{t_1 + t_2} \end{pmatrix} \qquad (A.B.18)$$

We can now calculate our household group specific demand, scaled to GLORIA:

$$\boldsymbol{r} = \begin{pmatrix} \frac{h_{total}}{t_{total}} & 0 & 0 \\ 0 & \frac{h_3}{t_3} & 0 \\ 0 & 0 & \frac{h_1 + h_2}{t_1 + t_2} \end{pmatrix} * \begin{pmatrix} f_1 \\ f_2 \\ f_3 \end{pmatrix} = \begin{pmatrix} \frac{h_{total}}{t_{total}} * f_1 \\ \frac{h_3}{t_3} * f_2 \\ \frac{h_1 + h_2}{t_1 + t_2} * f_3 \end{pmatrix} \qquad (A.B.18)$$

Concordance Table

We create our concordance table by working through the UN ISIC classification guideline (UNSD, 2008) and the COICOP classification guideline (UNSD, 2018) and defining which COICOP level 3 categories to match with each ISIC sector. Table A2.2 provides an overview.

Table TAB1: GLORIA – COICOP Concordance

GLORIA Sector	*COICOP Category*
Agriculture	*HE0933, HE0934*
Forestry	*HE0454*
Fishing	
Coal extraction	*HE0454*
Petroleum extraction	
Gas extraction	
Other mining & quarrying	
Meat	*HE0112*
Fish	*HE0113*
Cereals	*HE0111*
Veg	*HE0117*
Fruit	*HE0116*
Other food	*HE0114, HE0115, HE0118, HE0119*
Dairy	*HE0114*
Beverage	*HE0121, HE0122, HE0211, HE0212, HE0213*
Tobacco	*HE0220*
Textiles & leather	*HE0311, HE0312, HE0313, HE0321, HE0512, HE0520, HE0561*
Sawmill, pulp, paper	*HE0431, HE056, HE0954*
Printing	*HE0951, HE0952, HE0953, HE0954*
Coke oven products	*HE0454*
Refined petroleum products	*HE0453, HE0722*
Fertilizers	*HE0933*
Other chemicals	*HE0561, HE1213*
Pharma	*HE0611*
Paint, glues, detergents, other	*HE0431, HE0561*
Rubber & plastic	*HE0431, HE0540, HE0552, HE0561, HE0612, HE0721, HE0931, HE1213*
Cement, lime and plaster products	*HE0431*
Other non-metallic minerals	*HE0431, HE0540*
Basic metals	
Fabricated metal products	*HE0431, HE0531, HE0540, HE0522, HE0561, HE1213*
Machinery and equipment	*HE0551, HE0921*
Motor vehicles & transport equip	*HE0711, HE0712, HE0713, HE0714, HE0721, HE0921*
Repair and installation of machinery	*HE0923*
Computers, electronics & optical	*HE0613, HE0820, HE0911, HE0912, HE0913, HE0914, HE0922, HE0931, HE1212, HE1231*
Electrical equipment	*HE0431, HE0531, HE0532*
Furniture & other manuf	*HE0511, HE0613, HE0721, HE0922, HE0932, HE0954, HE1231*
Electric power	*HE0451*
Gas supply	*HE0452*
Water & sewage	*HE0441, HE0443, HE0455*
Waste & recycling	*HE0442*
Construction	*HE0432*
Wholesale and retail trade; repair of motor vehicles and motorcycles	*HE0111, HE0112, HE0113, HE0114, HE0115, HE0116, HE0117, HE0118, HE0119, HE0121, HE0122, HE0211, HE0212, HE0213, HE0220, HE0311, HE0312, HE0313, HE0321, HE0431, HE0453, HE0454, HE0511, HE0512, HE0520, HE0531, HE0532, HE0540, HE0551, HE0552, HE0561, HE0611, HE0612, HE0613, HE0711, HE0712, HE0713, HE0714, HE0721, HE0722, HE0723, HE0820, HE0911, HE0912, HE0913, HE0914, HE0921, HE0922, HE0931, HE0932, HE0933, HE0934, HE0951, HE0952, HE0953, HE0954, HE1212, HE1213, HE1231, HE1232*
Road transport	*HE0732, HE0735, HE0736, HE0960*
Rail transport	*HE0731, HE0735, HE0736, HE0960*
Pipeline transport	
Water transport	*HE0734, HE0735, HE0736, HE0960*
Air transport	*HE0733, HE0735, HE0736, HE0960*
Services to transport	*HE0731, HE0732, HE0733, HE0734, HE0735, HE0736, HE0960*
Postal & courier	*HE0810*
Hospitality	*HE0960, HE1111, HE1112, HE1120*
Publishing	*HE0951, HE0952, HE0953, HE0954*
Telecomm	*HE0830*
IT	*HE0830*

Finance & Insurance	*HE1252, HE1253, HE1254, HE1255, HE1262*
Property and real estate	*HE0411, HE0412, HE0421, HE0422*
Government; social security; defence; public order	
Education	*HE1010, HE1020, HE1030, HE1040, HE1050*
Human health and social work activities	*HE0621, HE0622, HE0623, HE0630, HE1240*
Arts, entertainment and recreation	*HE0941, HE0942, HE0960*
Other services	*HE0314, HE0322, HE0444, HE0513, HE0533, HE0562, HE0723, HE0724, HE0915, HE0923, HE0935, HE1211, HE1231, HE1232, HE1270*

Matching of Household Satellites

GLORIA satellites are provided for industries as well as for final consumption accounts. Final consumption satellites relate to environmental and social externalities that are caused directly by household consumption. They are not included in the economic value creation process captured by the input-output matrix and are therefore not considered as embodied in the consumption of goods and services in GLORIA. For CO_2 emissions, direct household externalities are limited to two IPCC emission categories, namely 1A3B (energy emissions from fuel combustion in road transport – essentially fuel for households' personal vehicles) and 1A4 (energy emissions from fuel combustion in other sectors – essentially other fuels that households burn).

We allocate these household emissions directly to household quantiles by imposing household expenditure for COICOP category HE0722 (fuels and lubricants for personal transport equipment) as a key to allocate IPCC category 1A3B emissions, and the sum of household expenditure for COICOP categories HE0452 (gas), HE0453 (liquid fuels), and HE0454 (solid fuels) as a key to allocate IPCC category 1A4 emissions.

Code

Matching scripts are available on the project repository, subdirectory datamatch/3_hbs_gloria (https://github.com/jmmnmbu/ecp_distrib/tree/main/datamatch/3_hbs_gloria). Access available upon request.

References

Eurostat (2023). *Microdata HBS (Household Budget Surveys) – Scientific Use Files.* Downloaded from www.circabc.europa.eu (last accessed 30 October 2023)

UNSD (2018). *Classification of Individual Consumption According to Purpose (COICOP) 2018*. Statistical Papers Series M no. 99. Downloaded from https://unstats.un.org/unsd/classifications/unsdclassifications/COICOP_2018_-_pre-edited_white_cover_version_-_2018-12-26.pdf (last accessed 16 November 2023)

UNSD (2008). International Standard Industrial Classification of All Economic Activities (ISIC). Statistical Papers Series M No. 4, Rev.4. Downloaded from https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf (last accessed 16 November 2023)

Appendix C

Description

We use Additive Structural Decomposition Analysis to disentangle the contributions of individual determinants to a total change, in our case the determinants of incidence, which we also call relative carbon cost. Recall our function to compute the outcome:

$$rcc = (diag(\boldsymbol{e}) * \boldsymbol{p})^T * \boldsymbol{L} * \boldsymbol{y} * a^{-1} + \boldsymbol{h}^T * \boldsymbol{k} * a^{-1} \qquad (A.C.1)$$

Where bold small letters are vectors, bold capital letters are matrices, and others are scalars. We follow the algorithm developed by Wood & Lenzen (2006) to deal with zero value problems. An application for energy use based on input-output data from Brazil has been done by Wachsmann et al. (2009). We want to decompose the change in relative carbon costs between two steps 1 and 0 into individual additive components, so our objective function is:

$$\Delta rcc = \Delta rcc(\boldsymbol{e}) + \Delta rcc(\boldsymbol{p}) + \Delta rcc(\boldsymbol{L}) + \Delta rcc(\boldsymbol{y}) + \Delta rcc(a^{-1}) + \Delta rcc(\boldsymbol{h}) + \Delta rcc(\boldsymbol{k}) \qquad (A.C.2)$$

The first step to decompose Δrcc is to express the total differential of relative carbon cost as the sum of all its partial differentials, using the chain rule.

$$drcc = \frac{\partial rcc}{\partial \boldsymbol{e}} d\boldsymbol{e} + \frac{\partial rcc}{\partial \boldsymbol{p}} d\boldsymbol{p} + \frac{\partial rcc}{\partial \boldsymbol{L}} d\boldsymbol{L} + \frac{\partial rcc}{\partial \boldsymbol{y}} d\boldsymbol{y} + \frac{\partial rcc}{\partial a^{-1}} da^{-1} + \frac{\partial rcc}{\partial \boldsymbol{h}} d\boldsymbol{h} + \frac{\partial rcc}{\partial \boldsymbol{k}} d\boldsymbol{k} \qquad (A.C.3)$$

The total difference in our outcome variable is its end value subtracted by its original value. This total difference can be approximated as the sum of all infinitesimally small changes by integrating across its total differential.

$$\Delta rcc = rcc_1 - rcc_0 = \int_{rcc_0}^{rcc_1} drcc \qquad (A.C.4)$$

If we assume all factors to be independent, we can expand this last expression as:

$$\Delta rcc = \int_{\boldsymbol{e_0}}^{\boldsymbol{e_1}} \frac{\partial rcc}{\partial \boldsymbol{e}} d\boldsymbol{e} + \int_{\boldsymbol{p_0}}^{\boldsymbol{p_1}} \frac{\partial rcc}{\partial p} d\boldsymbol{p} + \int_{\boldsymbol{L_0}}^{\boldsymbol{L_1}} \frac{\partial rcc}{\partial \boldsymbol{L}} d\boldsymbol{L} + \int_{\boldsymbol{y_0}}^{\boldsymbol{y_1}} \frac{\partial rcc}{\partial \boldsymbol{y}} d\boldsymbol{y} + \int_{{a^{-1}}_0}^{{a^{-1}}_1} \frac{\partial rcc}{\partial a^{-1}} da^{-1} + \int_{\boldsymbol{h_0}}^{\boldsymbol{h_1}} \frac{\partial rcc}{\partial \boldsymbol{h}} d\boldsymbol{h} + \int_{\boldsymbol{k_0}}^{\boldsymbol{k_1}} \frac{\partial rcc}{\partial \boldsymbol{k}} d\boldsymbol{k} \qquad (A.C.5)$$

Using the first term in A4.5 as an example and changing notation to make the computational loops intuitive to read:

$$\Delta rcc(e) = \int_{e_0}^{e_1} \frac{\partial rcc}{\partial e} de = e^1 pLya^{-1} - e^0 pLya^{-1} = \sum_{no} e_n^1 p_n L_{no} y_o a^{-1} - e_n^0 p_n L_{no} y_o a^{-1}$$
$$= \sum_{no} (e_n^1 - e_n^0) * p_n L_{no} y_o a^{-1} = \sum_{no} \Delta e_n * p_n L_{no} y_o a^{-1} \qquad (A.C.6)$$

Now we make a modification, extending nominator and denominator by e_n:

$$\Delta rcc(e) = \sum_{no} \frac{\Delta e_n}{e_n} * e_n p_n L_{no} y_o a^{-1} \qquad (A.C.7)$$

At this point, we need to decide which values to impose as weights when calculating our individual contributions. The suggestion by Ang & Choi (1997) and Ang & Liu (2001) is to use the logarithmic mean formulation as a weight, which in our case boils down to:

$$e_n = \frac{e_n^1 - e_n^0}{\ln(e_n^1) - \ln(e_n^0)} = \frac{\Delta e_n}{\Delta \ln(e_n)} \qquad (A.C.8)$$

And:

$$e_n p_n L_{no} y_o a^{-1} = \frac{\Delta(e_n p_n L_{no} y_o a^{-1})}{\Delta(\ln e_n p_n L_{no} y_o a^{-1})} \qquad (A.C.9)$$

Substituting A4.8 and A4.9 into A4.7 and rearranging terms gives us the LMDI formulation of the contribution of changing emission intensities:

$$\Delta rcc(e) = \sum_{no} \frac{\Delta(e_n p_n L_{no} y_o a^{-1})}{\Delta(\ln e_n p_n L_{no} y_o a^{-1})} * \ln \frac{e_n^1}{e_n^0} \qquad (A.C.10)$$

Accordingly, the contribution of changing carbon prices on sectors is:

$$\Delta rcc(p) = \sum_{no} \frac{\Delta(e_n p_n L_{no} y_o a^{-1})}{\Delta(\ln e_n p_n L_{no} y_o a^{-1})} * \ln \frac{p_n^1}{p_n^0} \qquad (A.C.11)$$

The contribution of changing economic structures is:

$$\Delta rcc(L) = \sum_{no} \frac{\Delta(e_n p_n L_{no} y_o a^{-1})}{\Delta(\ln e_n p_n L_{no} y_o a^{-1})} * \ln \frac{L_{no}^1}{L_{no}^0} \qquad (A.C.12)$$

The contribution of changing consumption bundles is:

$$\Delta rcc(y) = \sum_{no} \frac{\Delta(e_n p_n L_{no} y_o a^{-1})}{\Delta(\ln e_n p_n L_{no} y_o a^{-1})} * \ln \frac{y_o^1}{y_o^0} \qquad (A.C.13)$$

The contribution of changing totals scales of consumption is:

$$\Delta rcc(a^{-1}) = \sum_{no} \frac{\Delta(e_n p_n L_{no} y_o * a^{-1})}{\Delta(\ln e_n p_n L_{no} y_o a^{-1})} * \ln \frac{a^{-1^1}}{a^{-1^0}} + \sum_{v} \frac{\Delta(h_v k_v a^{-1})}{\Delta(\ln h_v k_v a^{-1})} * \ln \frac{a^{-1^1}}{a^{-1^0}} \qquad (A.C.14)$$

The contribution of changing direct household emissions is:

$$\Delta rcc(h) = \sum_{v} \frac{\Delta(h_v k_v a^{-1})}{\Delta(\ln h_v k_v a^{-1})} * \ln \frac{h_v^1}{h_v^0} \qquad (A.C.15)$$

And the contribution of changing carbon prices on direct household emissions is:

$$\Delta rcc(h) = \sum_{v} \frac{\Delta(h_v k_v a^{-1})}{\Delta(\ln h_v k_v a^{-1})} * \ln \frac{k_v^1}{k_v^0} \qquad (A.C.16)$$

We run these decompositions for each time step and each household quantile in each country.

Code

Decomposition computations are available on the project repository, subdirectory decomp (https://github.com/jmmnmbu/ecp_distrib/tree/main/decomp). Access available upon request.

References

Ang, B. W., & Choi, K.-H. (1997). Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method. *The Energy Journal*, *18*(3), 59–73. Retrieved from https://www.jstor.org/stable/41322738

Ang, B. W., & Liu, F. L. (2001). A new energy decomposition method: perfect in decomposition and consistent in aggregation. *Energy*, *26*(6), 537–548. Retrieved from https://doi.org/10.1016/S0360-5442(01)00022-6

Wachsmann, U., Wood, R., Lenzen, M., Schaeffer, R. (2009). Structural decomposition of energy use in Brazil from 1970 to 1996. *Applied Energy 86*, 578-587. https://doi.org/10.1016/j.apenergy.2008.08.003

Wood, R. & Lenzen, M. (2006) Zero-value problems of the logarithmic mean divisia index decomposition method. *Energy Policy 34,* 1326-1331. https://doi.org/10.1016/j.enpol.2004.11.010

Appendix D

Introduction

As a basic analysis of general tendencies across countries and scenarios, this section contains results of some simple correlation analyses. The sample is a panel of cross-sections over three timesteps. It is not balanced due to missing Eurostat HBS data. Economic data is taken from the WorldBank API through R package wbstats. All other data comes from the results directory of this project.

Code

Regressions are available on the project repository, subdirectory results_hl3 (https://github.com/jmmnmbu/ecp_distrib/tree/main/results_hlr3). Access available upon request.

Regressivity in the Baseline

Here we regress regressivity in the baseline at country-level on economic indicators, namely:

- GDP per capita (PPP)
- Population size
- Carbon intensity of the economy (kg/USD)
- m_price (the emissions-weighted average carbon price in the economy, taking all sectors into account)
- h_price (the highest advertised carbon price in the economy, which is not applied uniformly across all sectors)

We test a linear model fit for each case.

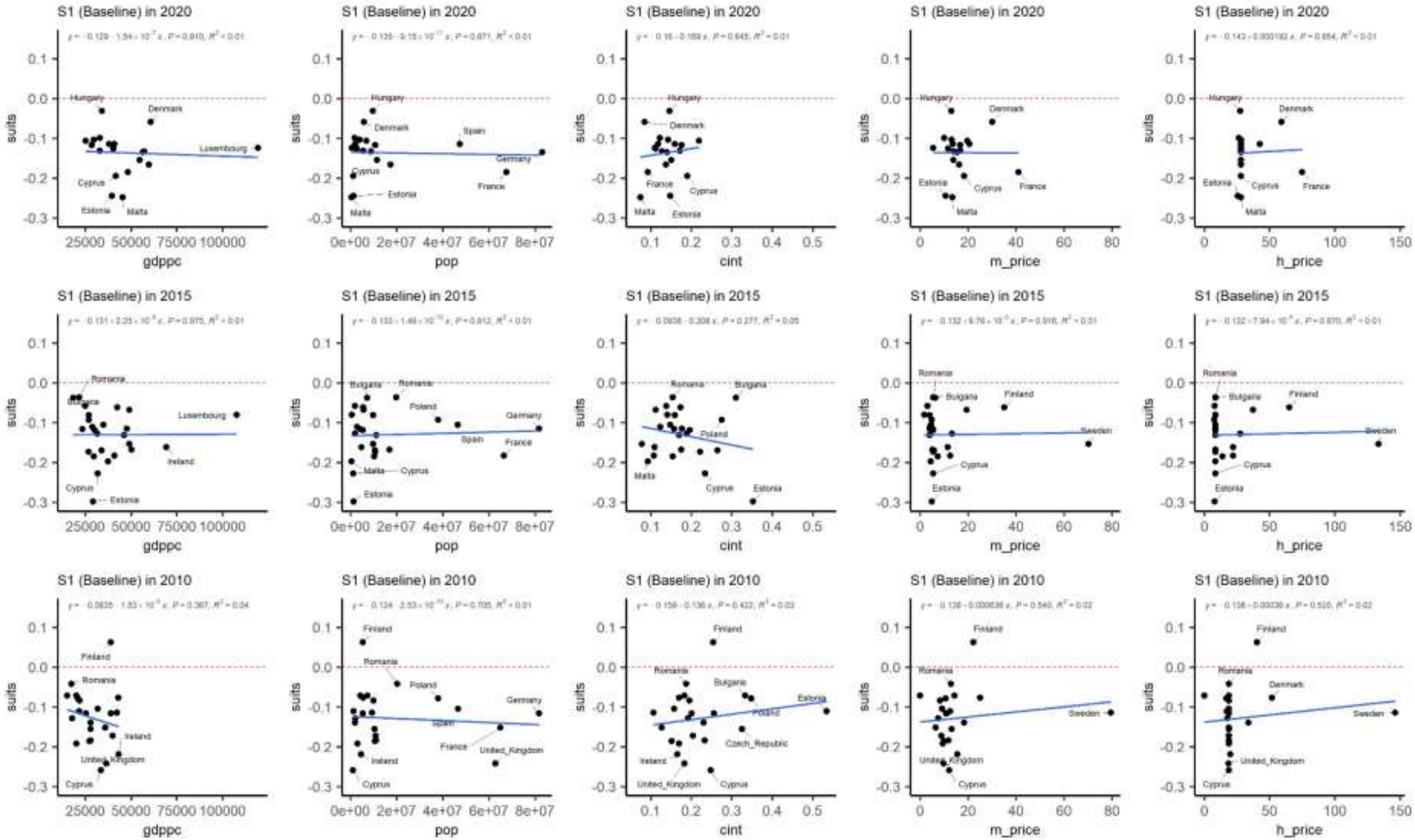

Figure FA.D.1: Correlation analysis regressivity (as measured by suits index) on economic indicators (columns) across years (rows).

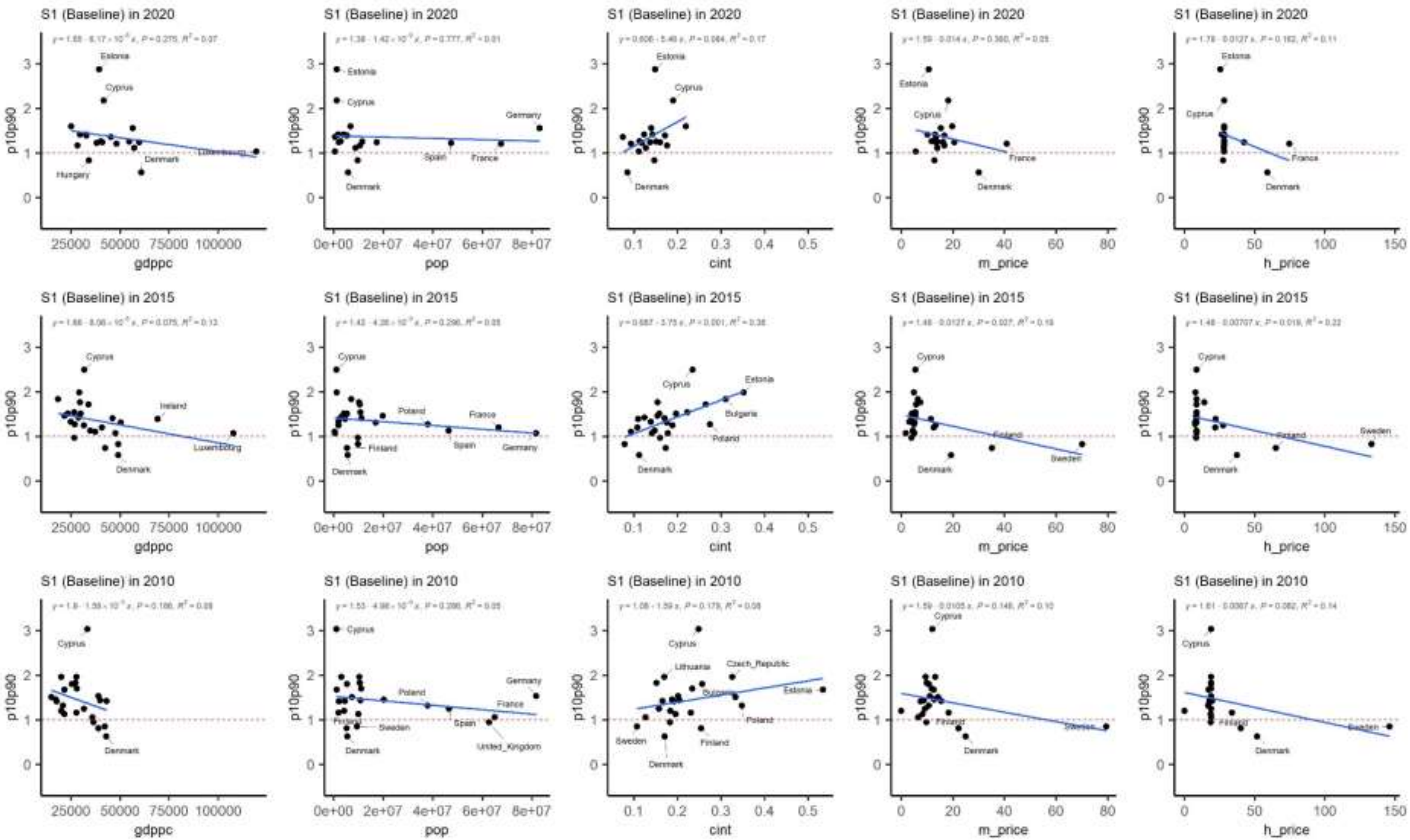

Figure FA.D.2: Correlation analysis regressivity (as measured by p10p90 index) on economic indicators (columns) across years (rows).

Regressivity Changes in Alternative Scenarios

Here we regress regressivity changes at country-level on economic indicators, namely:

- GDP per capita (PPP)
- Carbon intensity of the economy (kg/USD)
- m_price (the emissions-weighted average carbon price in the economy, taking all sectors into account)

We test a linear model fit for each case.

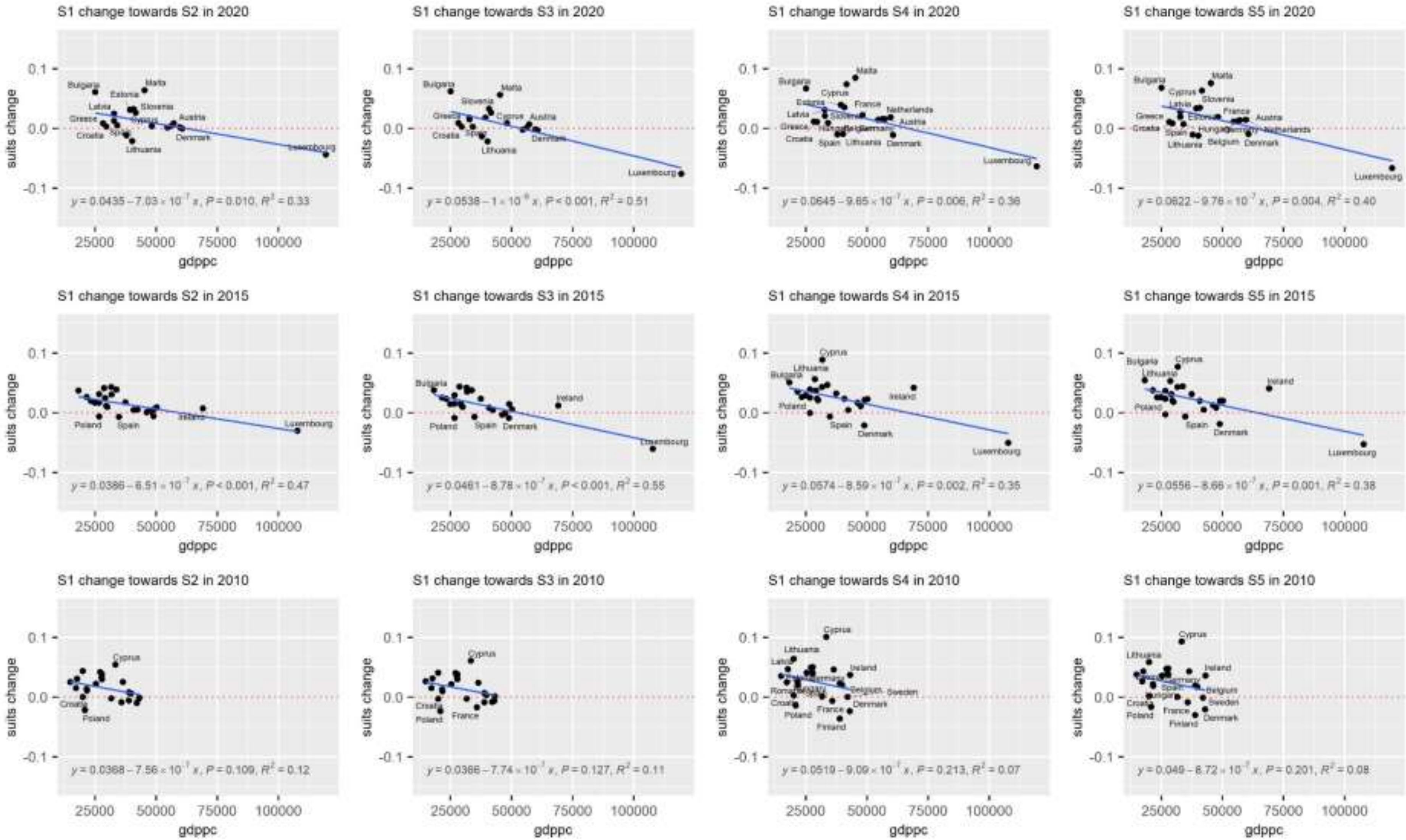

Figure FA.D.3: Correlation analysis regressivity change (as measured by suits index change) on GDP per capita, for different alternative scenarios (columns) across years (rows).

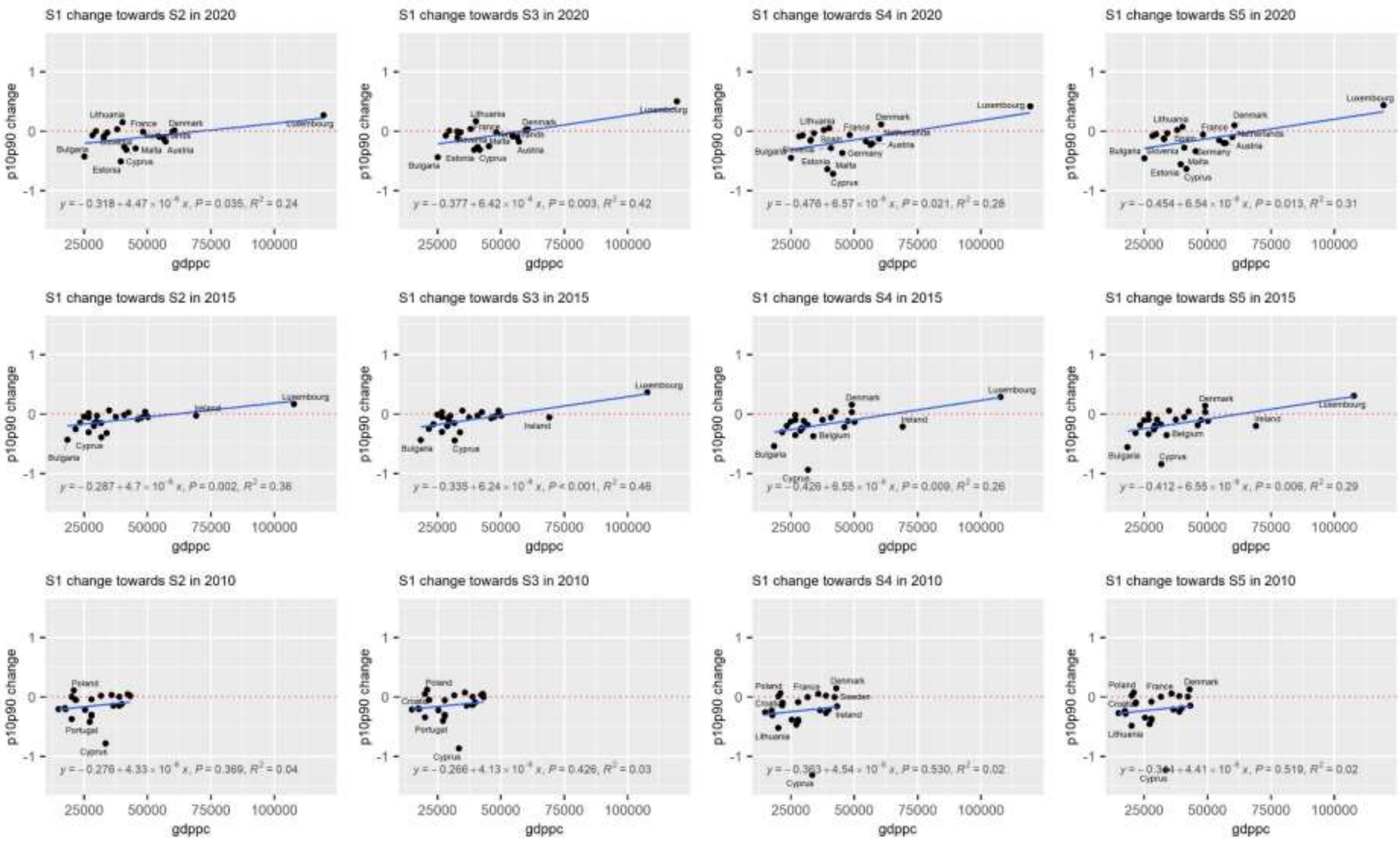

Figure FA.D.4: Correlation analysis regressivity change (as measured by p10p90 index change) on GDP per capita, for different alternative scenarios (columns) across years (rows).

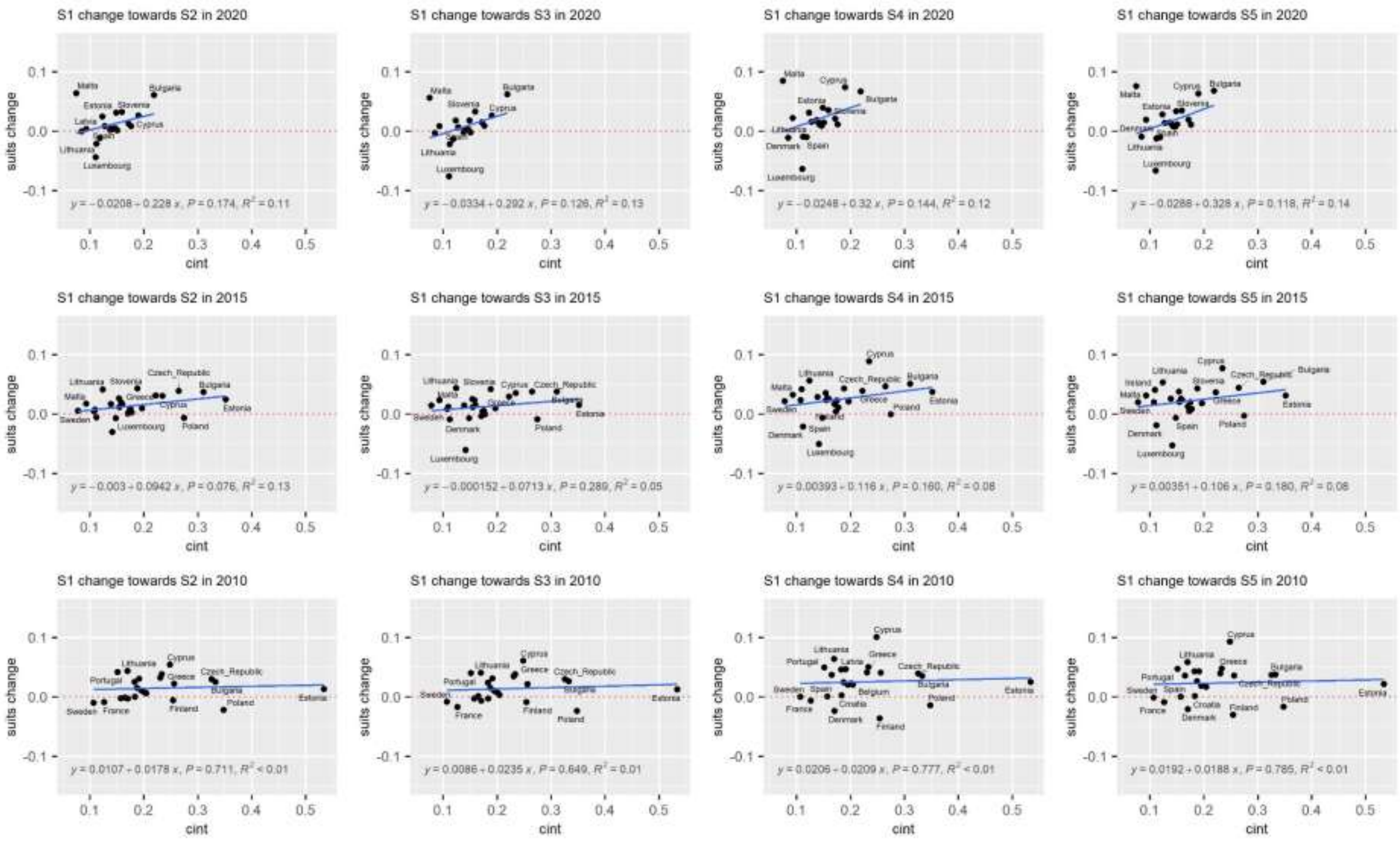

Figure FA.D.5: Correlation analysis regressivity change (as measured by suits index change) on carbon intensity, for different alternative scenarios (columns) across years (rows).

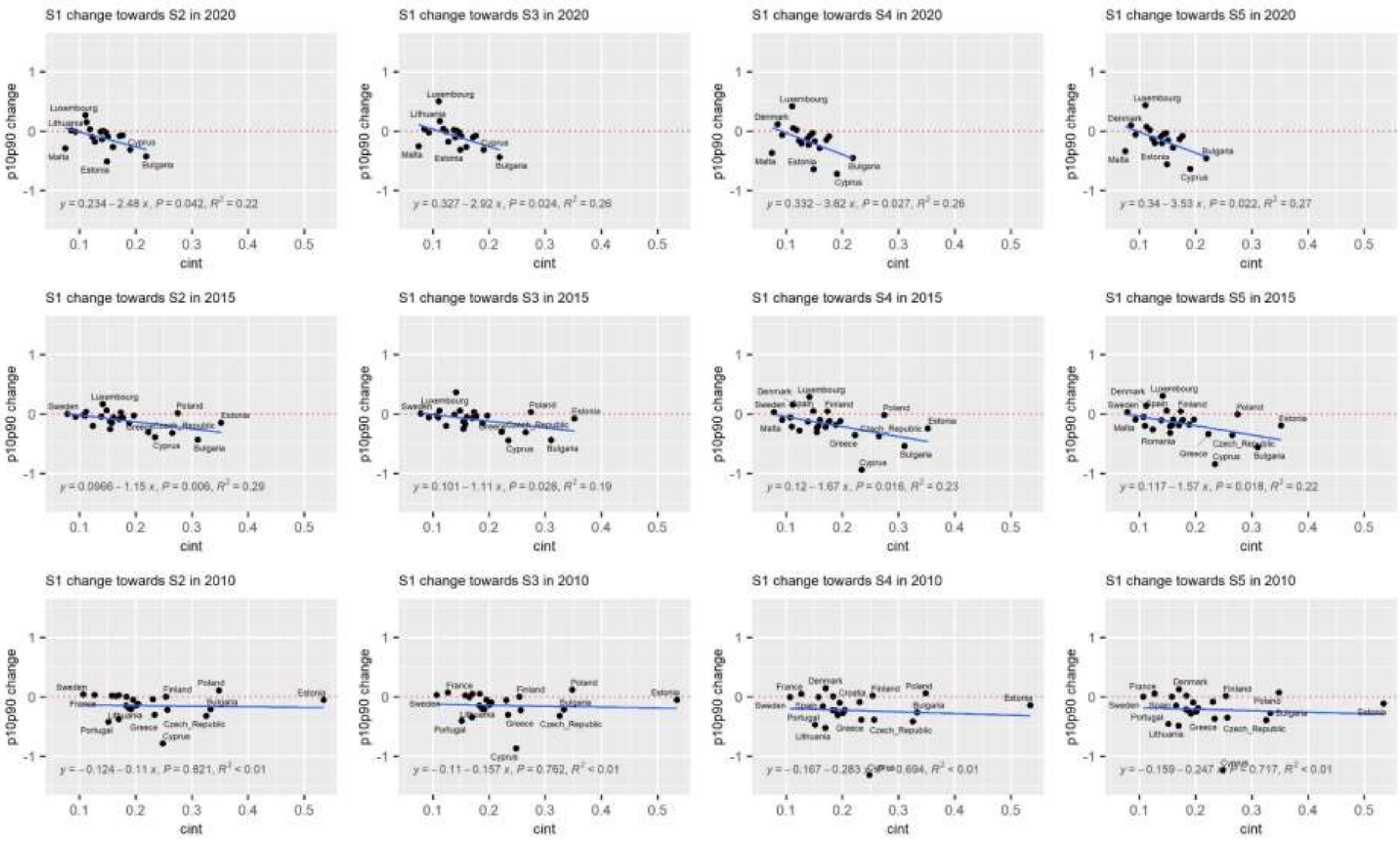

Figure FA.D.6: Correlation analysis regressivity change (as measured by p10p90 index change) on carbon intensity, for different alternative scenarios (columns) across years (rows).

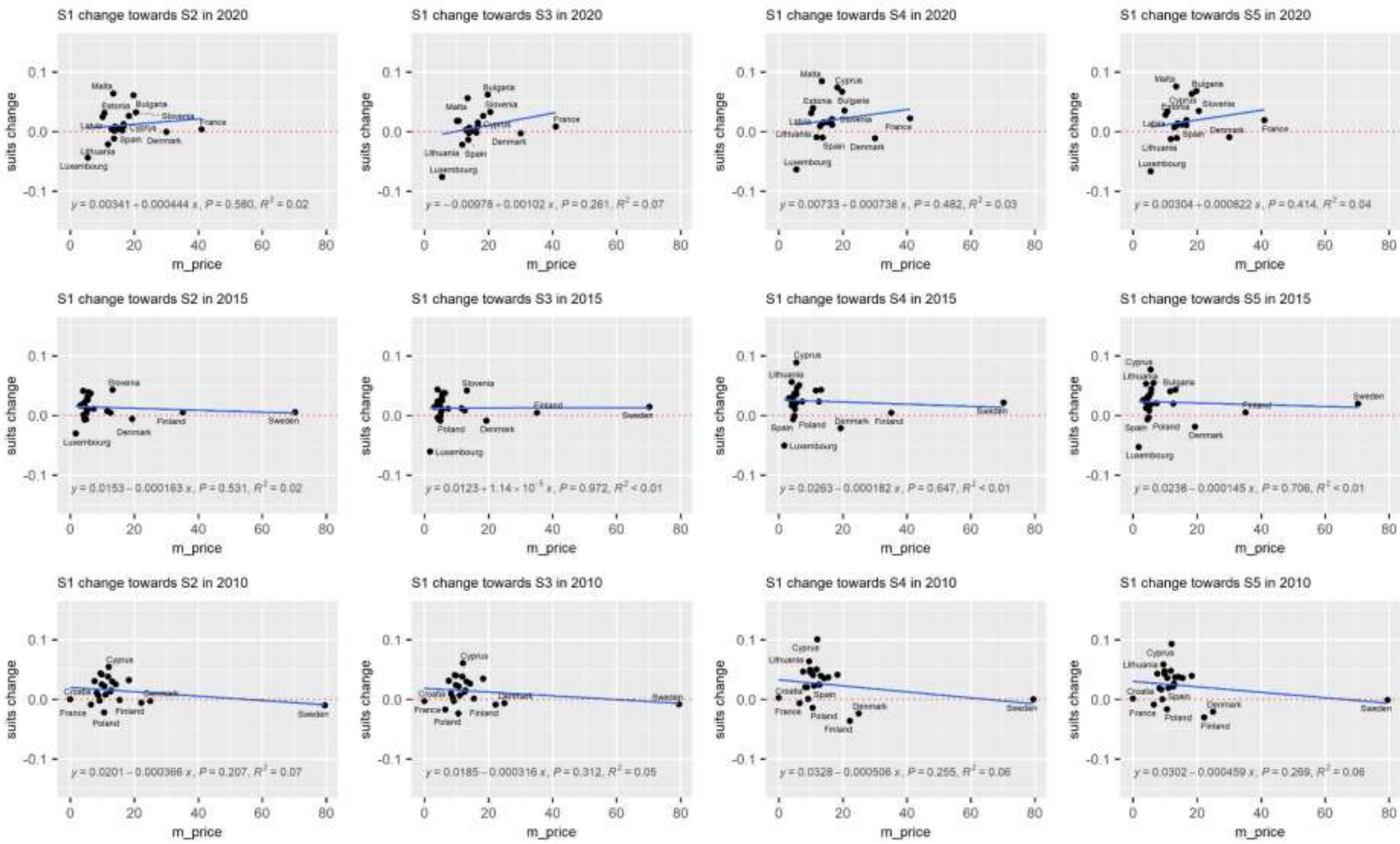

Figure FA.D.7: Correlation analysis regressivity change (as measured by suits index change) on average carbon price, for different alternative scenarios (columns) across years (rows).

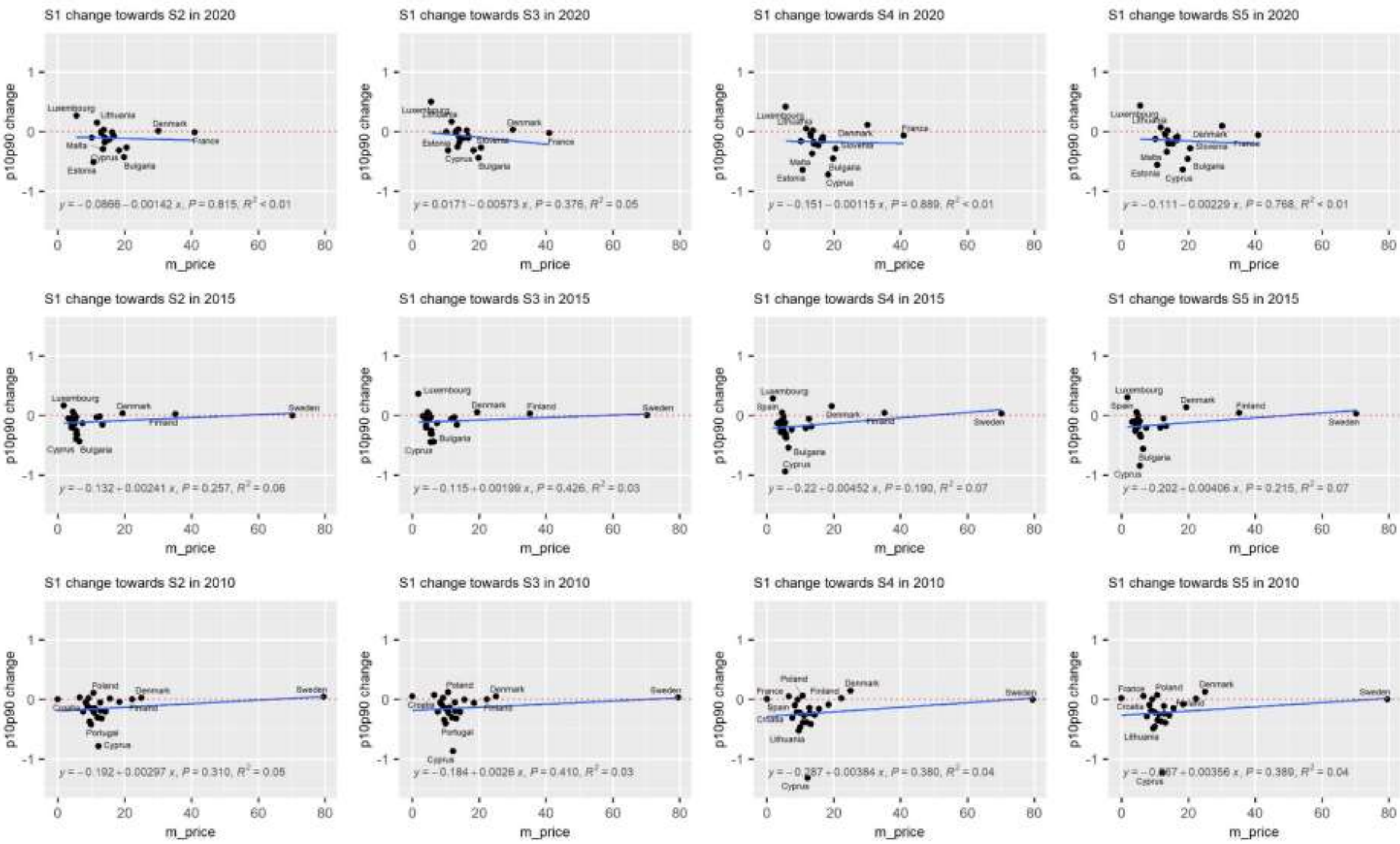

Figure FA.D.8: Correlation analysis regressivity change (as measured by p10p90 index change) on average carbon price, for different alternative scenarios (columns) across years (rows)