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# CARBON PRICING AND INEQUALITY:
# A NORMATIVE PERSPECTIVE

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**ABSTRACT**

Despite broad acceptance among economists, carbon taxes face persistent public resistance. We measure the sources and distribution of welfare losses from unexpected European carbon price changes by estimating their impact on consumer prices, labor income, financial wealth, and government transfers. A 1% carbon-policy-induced increase in energy prices leads to an average welfare loss of about 0.5%of a household's three-year consumption, primarily driven by indirect labor-income effects. Younger, poorer, and less educated households, especially in Southern and Eastern Europe, bear a disproportionate burden. These findings suggest public opposition to carbon taxes could stem from legitimate distributional concerns.

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# 1. Introduction

Climate change is perhaps humanity's greatest challenge. Economics offers a century-old fix: carbon taxes. While widely accepted in policy circles, practical attempts to implement carbon taxes have been consistently met with fierce resistance.[1] Why does a tax meant to solve one of humanity's greatest threats provoke such pushback? Are the average welfare losses from this specific tax unusually large, or does it disproportionately burden certain groups?

This paper attempts to quantify both the sources and the distribution of the welfare impacts of a carbon tax. By providing quantitative answers to the above questions, it also suggests strategies to mitigate resistance to carbon taxation.

To measure the sources and distribution of carbon-tax welfare effects, we adopt the "feasible set approach" developed in Del Canto et al. (2025). The main insight behind this technique is to apply the Envelope Theorem on a grand scale: the first-order impact of an unexpected tax change on any household is summarized by the change in the discounted present value of their future budgets. In turn, the effects on these budgets can be measured by estimating how the policy alters the consumption-basket prices, labor income, financial wealth, and government transfers. By measuring these budget changes, we obtain a "money-metric" welfare loss for each demographic of interest. A key advantage of this metric is that it is interpretable, being expressed in income units.[2] Moreover, it remains independent of specific preference assumptions, encompassing any theory in which we only require agents to optimize subject to budget constraints.

Although the framework is conceptually straightforward, its implementation requires careful empirical work. First, we must gather comprehensive historical data on consumption-basket prices and expenditure, labor income, financial wealth, and transfers across different demographics. Second, we need to estimate the causal effects of carbon price changes on these variables over time. This requires isolating variation that is plausibly exogenous to macroeconomic conditions. Carbon prices may rise precisely when the economy is booming and policy changes are more politically feasible. As a result, simple regressions of outcomes on carbon price changes risk conflating correlation with causation. To credibly estimate the dynamic causal effects, we need an instrument

[1] Notable examples of failed carbon prices include Australia's repeal of its carbon tax in 2014, the response of France in 2018 to the "yellow vest" protests, the failure of the Waxman-Markey cap-and-trade bill in the United States, and, more recently, the rollback of the Canadian consumer carbon tax in 2025.

[2] This follows a long literature in public finance, see e.g. Samuelson (1974), Deaton (1989), Saez and Stantcheva (2016).

for the carbon price.

We focus our measurements on Europe because, to date, it is the region of the globe that has advanced the furthest in putting a price on carbon. Specifically, we compile a new dataset combining rich information from three major European household surveys from Eurostat and the ECB. We then use this data to construct impulse response functions (IRFs) for the different variables for various demographic groups—four age groups, two education levels, three income brackets, and four geographic regions. As an instrument for unexpected carbon-tax changes, we follow the approach in Känzig (2023), exploiting high-frequency carbon futures price shifts around regulatory changes in the European carbon market to identify unexpected shocks to carbon prices. To the extent that economic conditions are priced in prior to the regulatory news, these shifts provide a plausibly exogenous source of variation in carbon prices. Using the identified carbon policy shocks, we estimate the IRFs of our variables of interest using local projections.

Our main findings are as follows. First, the overall welfare losses are unexpectedly large: a carbon-policy-induced increase in energy prices by 1% yields an average welfare loss of 250 euros, corresponding to about 0.5% of the average household's three-year consumption. These estimates, however, are subject to considerable uncertainty, with the 68% confidence bands ranging from 0.06% to 0.94%.

Second, the magnitude of these losses reflects the persistent nature of the energy price increase and its broad spillovers to other prices and labor market outcomes. When we decompose the sources of the welfare change, the direct effect—from higher consumption-basket prices—amounts to 0.19% of three years' consumption. Among the indirect effects (labor income, asset prices, and transfers), the respective impacts are 0.43%, –0.04%, and –0.07% of three-year consumption, making labor income the dominant contributor.

Third, turning to distributional patterns, we find pronounced differences across demographic and income groups. The direct effects on consumption-basket prices are broadly similar across households, but the indirect channels generate sizable welfare losses for younger, poorer, and less-educated households—primarily through reduced labor income. In contrast, older, wealthier, and better-educated households experience smaller losses, as the labor income channel plays a smaller role for them. These group differences are both economically meaningful and statistically significant.

We also document substantial regional heterogeneity, with Southern and Eastern Europe shouldering the largest welfare losses. Indirect effects through the labor market are again the primary driver, consistent with more rigid labor markets in these regions due to stronger employment protection and less flexible wage-setting institutions. Such rigidities may discourage hiring and extend unemployment spells, leading to sharper declines in labor income.

In sum, we document sizeable welfare impacts of carbon pricing alongside pervasive heterogeneity both within and across countries, with the data strongly rejecting the null hypothesis that carbon price shocks have uniform welfare effects across demographic groups and regions.

**Related literature.** This project contributes to a burgeoning literature on the impacts of carbon taxes and pricing. The literature has studied the effects of carbon pricing on emissions (Martin, De Preux, and Wagner, 2014; Andersson, 2019, among others), economic activity (Metcalf, 2019; Bernard and Kichian, 2021; Metcalf and Stock, 2023; Andersson, 2019; Känzig, 2023; Känzig and Konradt, 2024), and inflation (Konradt and Weder di Mauro, 2021; Bettarelli et al., 2025).

Our paper focuses squarely on inequality, as does a smaller subset of papers motivated by the same concerns. Andersson and Atkinson (2020), for example, studies the distributional effects of a sequence of carbon tax increases in transport fuel across different income groups.[3] Beznoska, Cludius, and Steiner (2012) use input-output tables to project increases in carbon taxes to electricity prices to different industry prices and present incidence measures on different consumers using German survey data. The approach in those papers is to estimate the direct effect on consumption-basket prices and, following Poterba (1989), to approximate lifetime effects using current expenditures.

Our methodology differs for three reasons. First, we consider surprise increases by instrumenting for shocks. Second, we also consider indirect effects (on income, asset prices, and transfers). Finally, we compute dynamic effects directly. Thus, a first contribution relative to this literature is the computation of IRFs to unexpected carbon price shocks of various budget-relevant variables for various demographics. While the methodology used to compute impulse responses follows Känzig (2023), we extend that analysis—originally focused on the United Kingdom—to encompass all European countries.

An important novel finding from our approach is that carbon price increases disproportionately affect lower-income households, but predominantly through the indirect labor income channel, which is not measured in studies that consider only direct effects. This finding is important because it corroborates recent survey evidence (see e.g. Drews and Van den Bergh, 2016; Dechezleprêtre et al., 2022).[4] Our quantitative finding suggests

[3] Kahn and Lall (2022) instead emphasize the distribution of holdings of durable assets exposed to carbon taxes, such as vehicles.

[4] However, survey evidence from Sweden indicates lesser distributional effects (Ewald, Sterner, and Sterner, 2022).

that surveys capture more than just perceptions and that the people who are most affected by the policies to mitigate climate change are the poor. In that sense, we also contribute to a broader literature in public finance on other Pigouvian taxes (e.g. Allcott, Lockwood, and Taubinsky, 2019).

A second contribution is translating our IRFs into welfare metrics for carbon price shocks. We apply the feasible set approach in Del Canto et al. (2025). This approach relates to several recent papers studying the welfare effects of price movements (Baqaee and Burstein, 2023; Dávila and Schaab, 2022; Fagereng et al., 2024). Baqaee, Burstein, and Mori (2022) and Jaravel and Lashkari (2022) provide methods to estimate the changes in consumer money-metric welfare over time under non-homothetic preferences. These studies focus on long-run welfare changes. The approach here focuses on short- to medium-term impacts on money-metric welfare. To our knowledge, we are the first to empirically estimate the incidence of carbon pricing on welfare.

Our IRFs and welfare loss estimates can be used as calibration inputs in various quantitative applications. For example, they can be used in quantitative public finance analysis. The theoretical foundation of carbon taxes rests on the targeting principle (Sandmo, 1975; Dixit, 1985). This principle states that one should always correct an externality by targeting its direct sources. This result extends to settings where distributional effects are present regardless of the available tax instruments (Kopczuk, 2003).[5] Public finance does emphasize that any undesirable distributional consequences should be offset, but to find the proper compensation, we need estimates like the ones provided in this paper.

A second use for the estimates here is as moment targets for quantitative-structural climate change models. Our IRFs can be used to discipline structural models that can speak to the longer-term impacts of carbon pricing and perform counterfactual analyses (e.g., Belfiori and Macera, 2025).

**Outline.** The paper proceeds as follows. In Section 2, we outline our approach to measuring the welfare impact of carbon price shocks. In Section 3, we discuss the data and our identification strategy. Section 4 presents the estimated impulse response functions and the budget sets. In Section 5, we present our welfare calculations. Section 6 concludes.

[5] Bovenberg and De Mooij (1994), Bovenberg and Goulder (1996) and Fullerton (1997) consider environmental taxes in general equilibrium contexts but under restricted sets of instruments.

# 2. A Feasible Set Approach to Welfare

Our methodology builds on the feasible set approach put forward in Del Canto et al. (2025). The key idea is that, up to first order, the welfare impact of a shock on households is summarized by the induced movements in their feasible sets: their budget constraint and borrowing constraints. We outline the approach below, leaving the formal setup and derivations to Appendix A.

The starting point is the household's expenditure and savings problem.[6] Households maximize their lifetime utility over consumption, labor, and asset holdings. They consume a basket of $J$ consumption goods, with expenditure $p_{jt}c_{j,t}$ at time $t$ for good $j$. They earn (after tax) labor income $W_tL_t$, deciding on $L_t$. In addition, they may receive some transfer income $T_t$. Lastly, they have a dynamic portfolio of $K$ assets, chosen optimally, each paying a dividend $D_{kt}$ and fetching a price $Q_{kt}$ at time $t$. These assets are varied: equities, debt, housing, cash, or durable goods, for example. Some of these assets could directly generate utility in addition to yields. One asset is risk-free one-period debt, which is used to discount future utility streams.

Our notion of welfare, following a long literature in public finance, is money-metric utility. We are interested in how many euros each individual would be willing to pay not to be exposed to the fundamental carbon price shock. Up to first order, the money-metric welfare change, denoted $dV$, is given by:

$$dV = \sum_t R_{0\to t}^{-1}\Bigg( \underbrace{-\textstyle\sum_j p_{jt}c_{jt}\Psi_t^{p,j}}_{\text{Consumption Price Changes}} + \underbrace{W_tL_t\Psi_t^W}_{\text{Labor Income Changes}} + \sum_k \Big[ \underbrace{N_{kt-1}D_{kt}\Psi_t^{D,k}}_{\text{Asset Income Changes}} - \underbrace{Q_{kt}\Delta N_{kt}\Psi_t^{Q,k}}_{\text{Asset Price Changes}} \Big] + \underbrace{T_t\Psi_t^T}_{\text{Transfer Income Changes}} \Bigg), \tag{1}$$

where $R_{0\to t}$ denotes the cumulative risk-free interest rate from time 0 to $t$, and $\mathbf{\Psi}_t^i$ is the impulse response of price $i \in \{p, W, D, Q, T\}$ to the carbon policy shock. Specifically, each element of this vector represents the log deviation of a variable from its pre-shock trend in period $t$ after a shock to the carbon price in period 0.

The welfare impact of a shock to the carbon price consists of five effects captured by

[6] To simplify the notation, we suppress indexing of the budget set variables by individual. However, everything below should be understood to vary across individuals; people who differ by age, income, and education will have different consumption plans, asset accumulation paths, and labor income processes.

each term inside the parentheses. The first term captures the rise in the prices of consumption goods in the agent's basket due to the carbon tax. The welfare impact of this price increase, in money-metric terms, weights the percentage change in the price of each good by the nominal expenditure on the good in a world absent the shock—this term has been the predominant focus of the literature following Poterba (1989). The second term captures the indirect effect on wages or labor income stemming from general equilibrium effects. Again, the welfare loss of these changes is summarized by weighting the impulse response of wages by total nominal labor income in the absence of the shock. The third is the analog of capital income. This term includes changes in dividends or interest rates. It also includes asset-price changes. As pointed out by Fagereng et al. (2024), the welfare impact of this change only depends on whether the agent is a *net buyer* or a *net seller* of the asset in a particular period.[7] The fourth term captures changes in transfer schemes, directly or indirectly, through indexed pension payments. Future price changes by time $t$ are discounted by the cumulative risk-free rate, $R_{0\to t}$.

We can obtain empirical counterparts to this decomposition following two steps: First, we estimate the response of the product and factor prices to shocks to the carbon price, using the methodology from Känzig (2023). We call the vector of these impulse response functions $\mathbf{\Psi}_t$. These are combined with life-cycle statistics on consumption expenditure ($p_{jt}c_{jt}$), labor income profiles ($W_tL_t$), asset income ($N_{kt-1}D_{kt}$) and asset accumulation profiles ($Q_{kt}\Delta N_{kt}$) and transfer profiles ($T_t$).

The advantage of this semi-structural approach is that we can be agnostic about many of the primitives of the household's problem. The result, however, leverages the envelope theorem and is thus only accurate for relatively small movements in carbon prices. Given that the shocks we consider are relatively small, we think this approach yields valuable insights. It is also important to note that up to a first order, behavioral responses are irrelevant for welfare, which is why no behavioral responses appear in (1).

Lastly, we note that the *benefits* of reduced carbon emissions appear nowhere in the welfare calculation. This is because we are only interested in the overall and distributional pecuniary costs of carbon taxes. The benefits of a better climate or disaster risk reductions do not appear here. The formula, however, may be useful to test if carbon taxes are set appropriately, provided that we have a measure of these benefits obtained elsewhere. Whether carbon taxes are set appropriately can be thought of in the following way: on

[7]The logic of this can be understood with an example. Suppose an older Spanish household is planning to sell down its equity holdings to fund its retirement. When the carbon price rises, equity prices fall. This causes a welfare loss in the period they were planning to sell their holdings, as they receive less cash and can purchase fewer consumption goods. The opposite logic holds for a younger household in the accumulation phase of life.

the margin, an additional euro of a carbon tax must balance the direct economic welfare effects in (1), with the additional reduction in CO2, multiplied by the marginal welfare gains of this reduction.

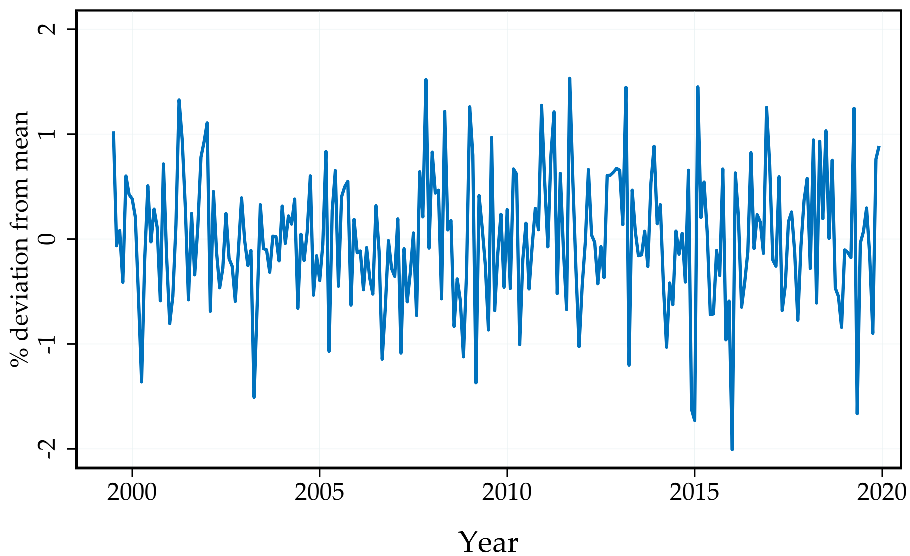
Before moving to calculate these welfare losses, it is worth discussing the limitations of this approach. First, the formula in (1) is a small-noise approximation around a zero-risk limit, in which both idiosyncratic and aggregate risk are taken to zero. In the real world, of course, individuals are subject to both. On the one hand, idiosyncratic risk can be handled in a completely general manner using the feasible set approach. To do so, one can adjust each price change (1) by the covariance of that price change with the marginal utility of consumption (see Appendix A for more details). In a sense, this "discounts" more heavily price changes in "risky" income streams. This is done in Del Canto et al. (2025), and they show that it makes little difference quantitatively. Applying their estimates of the appropriate adjustment factors in this context would not change the distributional comparisons meaningfully, but would attenuate the size of the welfare impacts somewhat. Large aggregate risk, on the other hand, is not well-handled by the framework. Given that fluctuations in carbon prices at current levels are unlikely to be major contributors to business cycle fluctuations, we are comfortable with the small-noise limit for this case; in other areas, it may be less suitable.

Second, the feasible set approach is best-suited to model shocks arising from the production side of the economy, or from policy variables. In general, if changes in key prices in the economy arise from preference changes—such as discount rate shocks, or changes in the relative preference for durable goods, as was seen in the COVID recession—then the formula in (1) no longer applies. Although such preference shocks are undoubtedly important for the macroeconomy, we view our application to carbon markets as a prime example of the areas in which this price-theoretic formulation can serve as a useful guide to distributional policy issues.

# 3. Data and Identification

We focus on measuring the welfare costs of carbon prices on European households. The EU is widely recognized as a leader in climate policy due to its comprehensive and ambitious strategies. The cornerstone of EU climate policy is the European Union Emission Trading System (EU ETS). It is the world's first major carbon market and remains one of the largest markets. Established in 2005, it covers more than 11,000 heavy energy-using installations, accounting for around 40% of the EU's greenhouse gas emissions.

Figure 1: Carbon policy shocks




*Notes:* The monthly carbon policy shock series from Känzig (2023), estimated based on an external instruments VAR for the European economy using the carbon policy surprise series as an instrument.

**Identification.** Carbon prices in the EU ETS are market prices, determined by the supply of emissions allowances and the demand for emissions. As in any market, distinguishing between demand and supply shocks poses identification challenges. Simply regressing outcome variables on carbon prices would therefore yield biased estimates of the effects of policies that restrict emissions. For example, carbon prices can decline in recessions, precisely when household income is falling. Thus, to estimate the dynamic causal effects of carbon policy, i.e., our IRF inputs, we need to isolate plausibly exogenous variation in carbon prices—specifically, changes in carbon prices driven by policy changes affecting the supply of emission allowances.

However, climate policy changes are not determined in a vacuum. Policymakers take economic conditions into account when formulating reforms of the carbon market. Thus, to adequately identify exogenous variation in policies, we employ the approach in Känzig (2023) which exploits institutional features of the carbon market combined with high-frequency information on carbon futures prices. The idea is to construct a series of carbon policy surprises by measuring how carbon futures prices change in a tight window around regulatory policy events that affect the supply or allocation of emission allowances. These surprises are then used as an instrument in a structural vector autoregression (VAR) model of the European economy to identify a monthly series of structural carbon policy shocks, $CPShock_t$. Figure 1 shows the identified shocks over our sample from 1999 to 2019.

**Local projections.** To analyze the effects of a carbon policy shock on prices and household incomes, we use local projections à la Jordà (2005). For each outcome variable of interest, $y_i$, we run the following set of regressions for $h = 0, \ldots, H$:

$$y_{i,t+h} - y_{i,t-1} = \beta^i_{h,0} + \psi^i_h CPShock_t + \beta^i_{h,1} \Delta y_{i,t-1} + \ldots + \beta^i_{h,p} \Delta y_{i,t-p} + \lambda^i_h d_t + \xi_{i,t,h}, \quad (2)$$

where $\psi^i_h$ is the effect on variable $i$ at horizon $h$. This approach follows Cloyne et al. (2023) and Drechsel (2023), and correctly recovers the dynamic causal effects of interest, provided the carbon policy shock is properly identified. Some of our outcome variables are only available at a quarterly frequency. However, we can still employ this approach: we aggregate the shock $CPShock_t$ to a quarterly series by summing over the respective months before running the local projections. In terms of controls, we include lags of the dependent variable, and $d_t$ includes a linear trend and a dummy for the peak of the European sovereign debt crisis from July 2011 to March 2012.

We normalize the IRFs to correspond to a carbon-policy-induced increase in the HICP energy component by 1% on impact. Based on the pass-through estimates in Känzig and Konradt (2024), this corresponds to an increase in EU ETS prices by around 2.5 EUR. Given the average ETS price over our sample period, this amounts to a 20% increase in carbon prices. Confidence bands are computed using the lag-augmentation approach (Montiel Olea and Plagborg-Møller, 2021), which accounts for serial correlation by augmenting the local projection with additional lags of the dependent variable. In conducting inference, we treat the carbon policy shock as observed.

For inference on the money-metric welfare changes in (1), we follow Del Canto et al. (2025): Specifically, we employ a parametric bootstrap drawing from the distribution of the estimated IRFs, taking the cross-sectional group shares as given.[8]

**Data.** To implement the feasible set approach, we have the following data requirements. First, we require time-series data on consumer prices and asset prices, all of which are readily available from national statistics and financial data providers. Second, we require life-cycle data on consumption expenditures by good, labor income profiles, asset income and accumulation profiles, and transfer profiles. These can be sourced from large-scale household surveys. Our formula for the money-metric welfare change (1) calls for the life-

[8] To construct the distribution of the estimated IRFs, we estimate their variance-covariance matrix, imposing block-wise uncorrelatedness across variables. We consider this a reasonable assumption, as the correlations across LP residuals are, on average, very low (around 0.16), and pairwise tests cannot reject zero correlation in the vast majority of cases. It is also a practical assumption, helping to avoid complications stemming from differences in estimation samples and sampling frequencies across variables.

cycle variables to be evaluated at the deterministic steady state. We approximate this by assuming that 2015 represents a stochastic steady state (i.e., is absent aggregate shocks), and further assuming that the stochastic steady state is "close" in the sense of household choice variables to the deterministic steady state.

Our sample includes countries in the euro area, all of which are subject to the European carbon market, spanning the period from 1999 to 2019.[9] We collect country-level time series on consumer prices from Eurostat. Specifically, the Harmonized Index of Consumer Prices (HICP) for the 12 main consumption categories according to the Classification of Individual Consumption by Purpose (COICOP). For asset income and price changes, we collect stock prices, dividends, bond prices, and house prices from the ECB. We assume that stock and bond markets are integrated, and we use euro area-wide data for these prices, while for house prices, we assume that markets are local and we collect country-specific data.

We complement this time-series data with household survey data covering the required parts of the household budget constraint. The challenge is that there is no single survey in Europe that spans all the information we need. Therefore, we combine granular information from a selection of European household surveys. Specifically, we use the Household Budget Survey (HBS) to obtain detailed information on household consumption baskets by demographic, the Statistics on Income and Living Conditions survey (SILC) for information on income, and the Household Finance and Consumption Survey (HFCS) for household portfolios. The former two surveys are available through Eurostat, while the latter is administered by the ECB. The SILC survey has coverage back to 2004 and includes rich information on labor and transfer income. We construct time series of labor income by different household groups to estimate the impulse responses based on the approach outlined above. Details on the data sources and construction are in Appendix B.

For the discount rate in (1), we use the 3M Euribor rate. We use the sample average of this series between 2004 and 2019, and then cumulate this value to get $R_{0\to t}$.

# 4. The Heterogeneous Impact of Carbon Policy

In this section, we provide evidence on the two key ingredients of our money-metric welfare calculations: the impulse responses to carbon policy shocks and the cross-sectional moments of household income, expenditure, and portfolio positions.

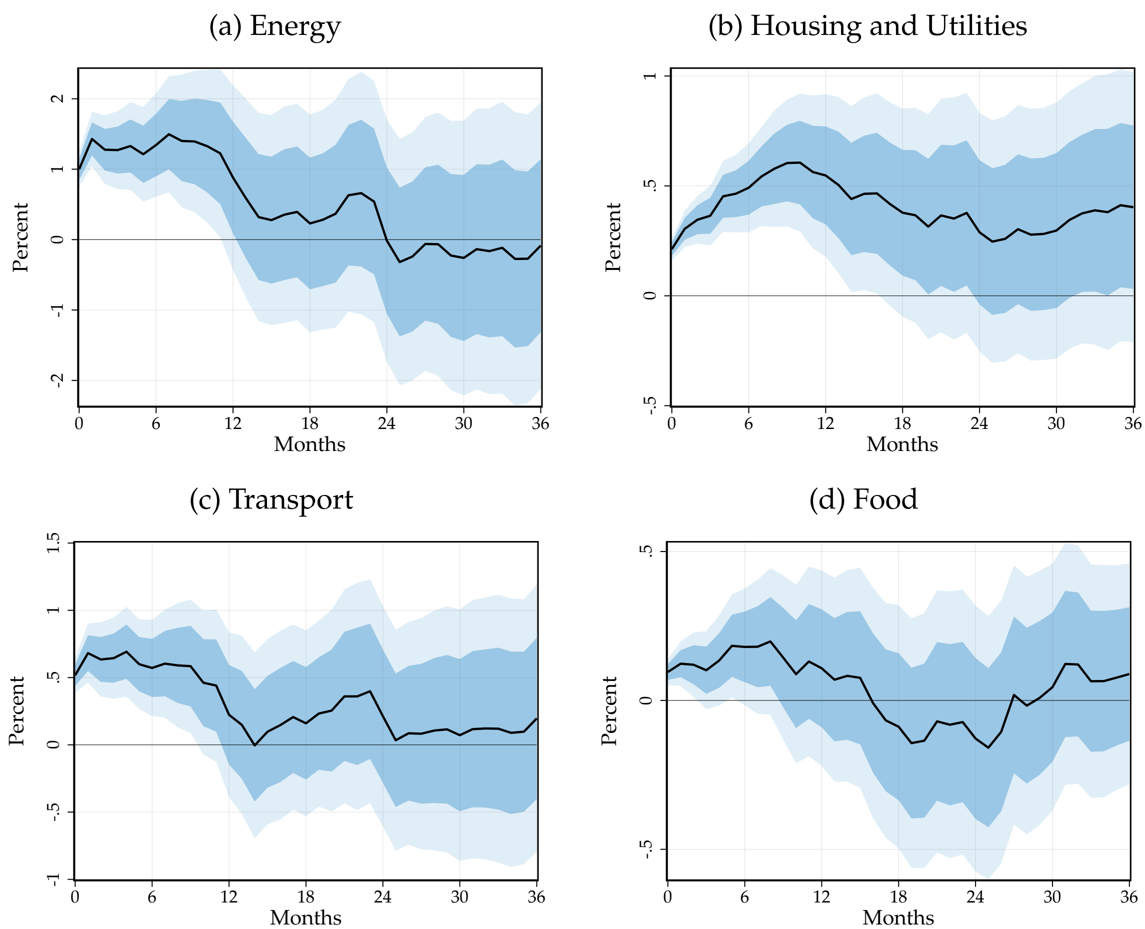
[9] Because we do not have all the required survey data for the Netherlands and Austria, these two countries are excluded from the analysis.

## 4.1. Dynamic Causal Effects of Carbon Policy Shocks

We start by discussing the estimated impulse responses to a carbon policy shock. Throughout, we report point estimates alongside 68% and 90% confidence bands.

**Consumer prices.** Figure 2 presents the responses of the energy component of the HICP, as well as HICP indices for housing and utilities, transport, and food. The identified shock leads to a significant increase in energy prices, which rise by 1% on impact and remain elevated for approximately a year before gradually returning to baseline. The response is consistent with the effect estimated in Känzig (2023), reflecting a strong pass-through from carbon prices to energy prices.

Figure 2: Responses of Selected Consumer Prices



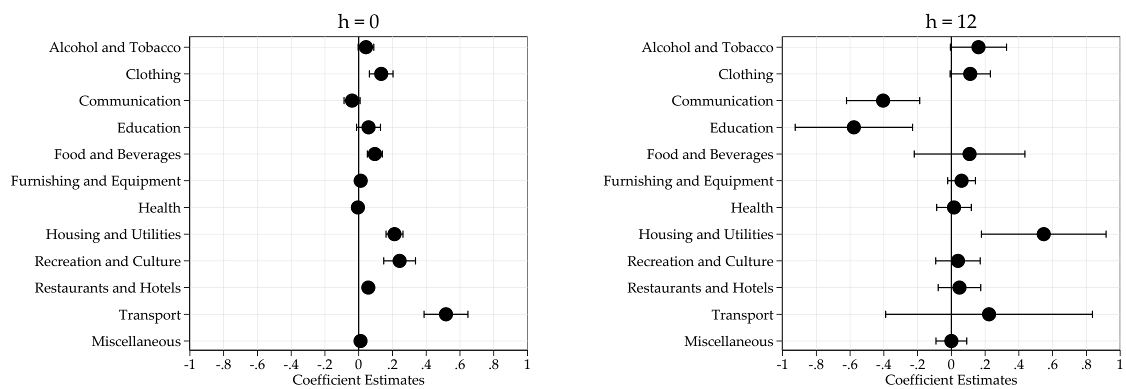

*Notes:* Impulse responses of selected HICP components, estimated using local projections (2) on the carbon policy shock from Känzig (2023). The responses are normalized to increase HICP energy by 1% on impact. Controls: 6 lags of the outcome variable, linear trend, and euro crisis dummy. The solid line is the point estimate, and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on a lag-augmentation approach.

Higher energy prices also spill over to an increase in other consumer prices, particularly in categories that directly include energy costs or are heavily dependent on energy. For instance, housing and utilities experience a significant and persistent price increase, with the effect still at approximately 0.5% three years after the shock. A similar pattern emerges for transport prices, which increase by 0.5% on impact but revert to baseline within a year. Although food and beverages do not directly include energy-related goods, they are heavily influenced by energy costs. Accordingly, food prices also exhibit a significant increase, although to a lesser extent.

Figure 3 displays the impact effect as well as the response after one year for the consumer prices for all 12 COICOP categories that we consider. In addition to the energy-related categories discussed earlier, we also observe significant price spillovers in restaurants and hotels, recreation and culture, and clothing. However, one year after the shock, most effects become insignificant. The main exceptions are housing and utilities, where prices remain significantly higher, and education and communication, where prices actually fall. Price declines in this context might be attributed to adverse general equilibrium effects via wages and employment, which put downward pressure on these prices.

Figure 3: Consumer Price Responses of all COICOP Categories

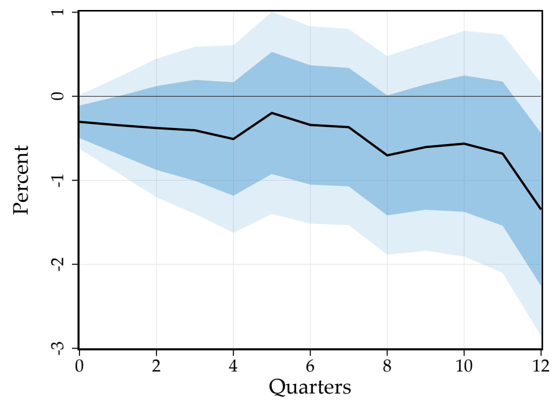
(a) Impact Response | (b) Response After 12 Months




*Notes:* Impulse responses of all 12 HICP components per COICOP classification at $h = 0$ and $h = 12$, estimated using local projections (2) on the carbon policy shock from Känzig (2023). Controls: 6 lags of the outcome variable, linear trend and euro crisis dummy. The responses are normalized to increase HICP energy by 1% on impact. Shown is the point estimate with 90% confidence bands.

**Labor income.** Figure 4 shows the average response of labor income. Labor income falls substantially after the shock, with a peak effect of about 1%. The response also features a considerable degree of persistence but is only imprecisely estimated.

Figure 4: Average Labor Income Response




*Notes:* Impulse responses of labor income, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 2 lags of the outcome variable, linear trend, and euro crisis dummy. The solid line is the point estimate, and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on a lag-augmentation approach.

However, this average response masks substantial heterogeneity across households. To explore potential heterogeneity, we group households by educational attainment (college vs. non-college educated) and income level (low income, defined as the lower quartile of the income distribution; middle income, defined as the middle 50%; and high income, defined as the upper quartile).

Figures 5a-b show the income responses by education level. We can detect meaningful differences: The response of the non-college-educated individuals displays a larger fall, with a peak effect in excess of 1%. The response looks fairly similar to the average labor income response, consistent with the fact that the majority of households do not have a college degree. By contrast, the response of college-educated individuals is more muted.

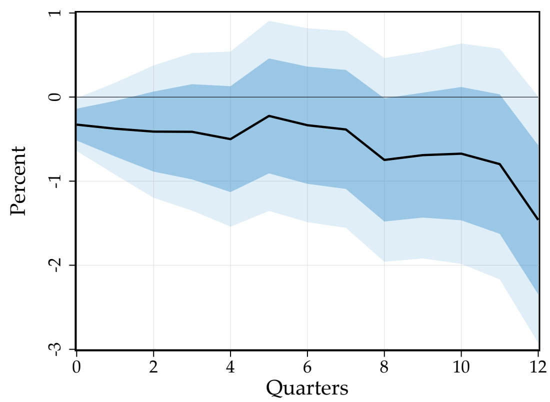
The heterogeneity is even starker by income levels. Figures 5c-e display the IRFs for the three income groups we consider. We find the strongest effect for low-income households, where incomes fall by around 2% to 4% over the three years of the estimated response. Interestingly, we also document a non-negligible fall for high-income households. Their labor income falls by about 1%. Middle-income households, on the other hand, appear to be more insulated. Their labor income falls by around 0.5-1%. These findings are consistent with results in Känzig (2023) for a sample of British households.

Compared to the results in Del Canto et al. (2025), which studies the impact of oil price shocks on U.S. households, we find more pronounced labor income responses and a greater degree of heterogeneity. These differences may reflect the relatively more rigid labor markets in Europe. While labor protection laws can shield incumbent workers by

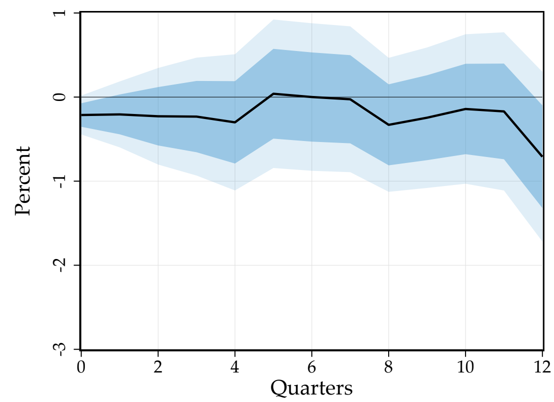
Figure 5: Labor Income Responses by Education and Income Groups

**Education**:

(a) Non-College Educated

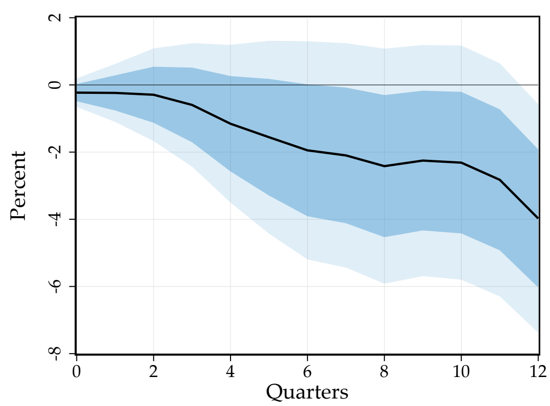



(b) College Educated

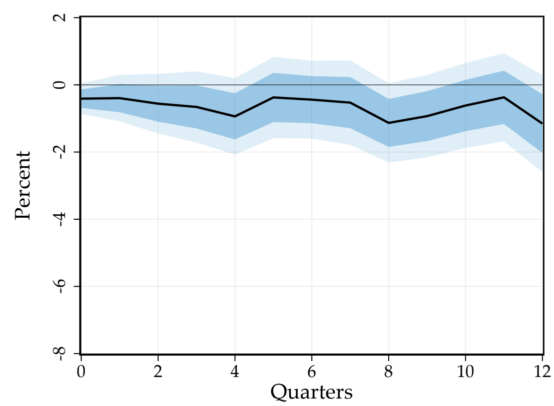



**Income**:

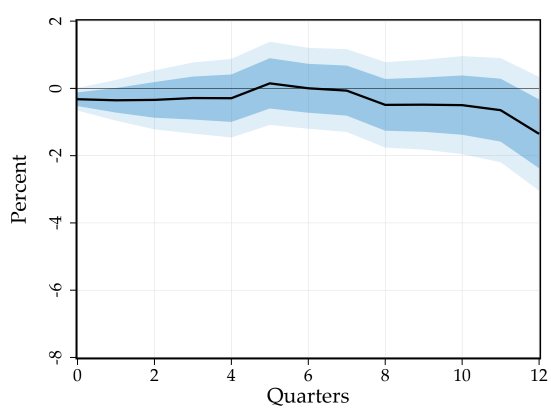
(c) Low Income




(d) High Income




(e) Mid Income




*Notes:* Impulse responses of labor income by education and income level, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 2 lags of the outcome variable, linear trend, and euro crisis dummy. The solid line is the point estimate, and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on a lag-augmentation approach.

limiting wage cuts and firing, they may also discourage hiring and prolong unemployment spells. As a result, total labor income may decline more in rigid labor markets, due to larger extensive-margin adjustments. This interpretation is consistent with the findings of Blanchard and Wolfers (2000), who emphasize the amplification role of labor market institutions in the transmission of shocks.

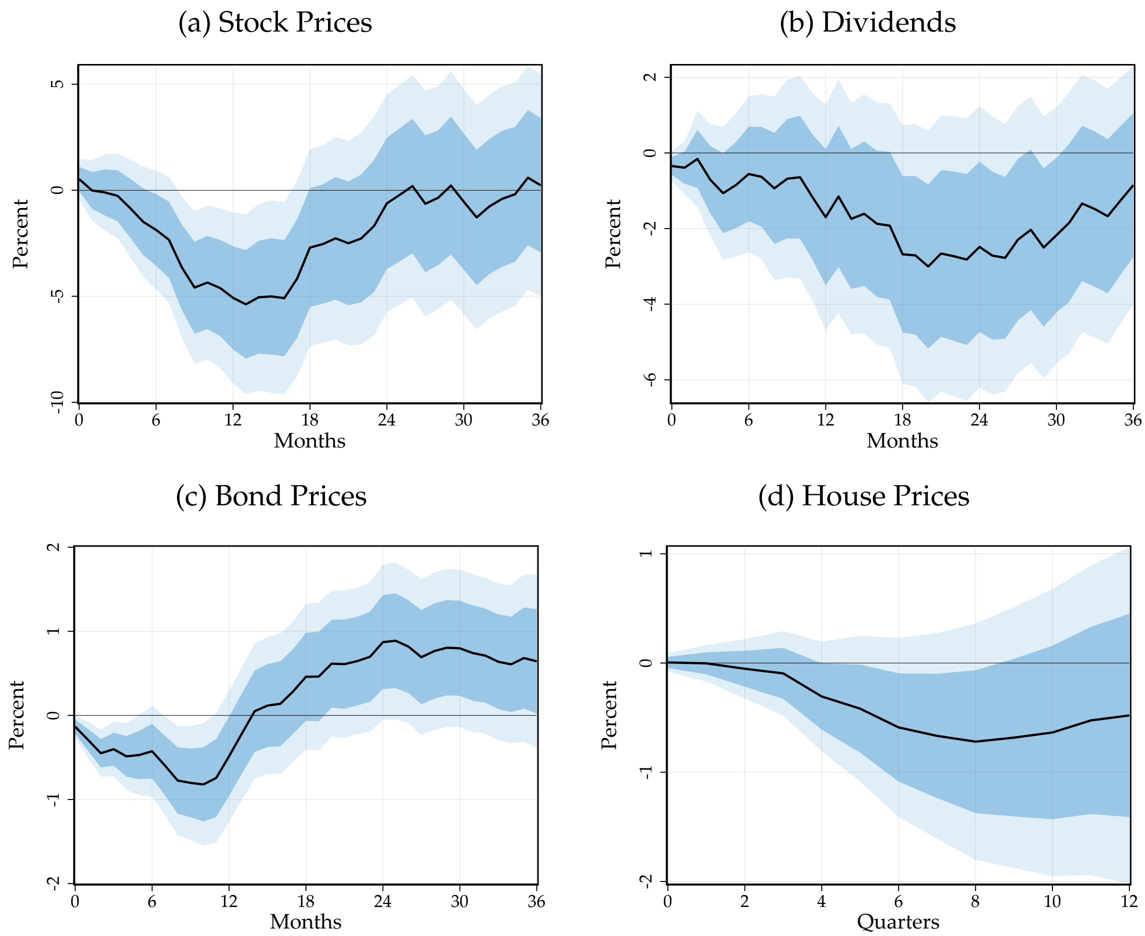
We do not find evidence for significant counter-cyclical transfers conditional on carbon policy shocks: transfer income tends to increase; however, the responses are generally not statistically significant. Pensions, on the other hand, tend to be indexed to inflation and increase after a carbon policy shock. We discuss the responses of pensions and transfer income in detail in Appendix C.2.

**Financial income.** Figure 6 reports the responses of asset prices to a carbon policy shock. Stock prices fall significantly, reaching a peak decline of about 5%. In turn, dividends respond more gradually, starting to decline considerably after about a year, with a drop of around 3%. The effect on bond prices is weaker, with bond prices declining in the first year, followed by a reversal. Finally, house prices decline substantially, but with a considerable lag.

From a pricing perspective, asset prices may decline due to higher discount rates and lower expected cash flows. For bonds and real estate, our interpretation is that the decline reflects a standard discounting channel: carbon policy increases headline inflation, which raises expectations of tighter monetary policy. As nominal and real interest rates rise, bond and home prices fall. This mechanism is consistent with the empirical findings in Känzig and Konradt (2024), who document the inflationary effects of carbon policy shocks in Europe, and Bettarelli et al. (2025), who find that carbon-tax shocks contribute to broader inflation—a phenomenon they term "greenflation."

Equity positions are even more affected, as they suffer not only from higher discounting but also from lower expected cash flows due to the macroeconomic impact of the shock. Importantly, however, the carbon policy shock is beneficial to demographic groups planning to accumulate equity, as these assets become cheaper after the shock. Thus, the strength of the portfolio channel depends critically on who currently holds equities and who intends to acquire them. A similar logic applies to bonds and housing: those planning to buy homes and bonds benefit, as they can do so at lower prices following the shock.

Figure 6: Asset Price Responses




*Notes:* Impulse responses of stock prices, dividends, bond prices, and house prices, estimated using local projections (2) on the carbon policy shock from Känzig (2023). The responses are normalized to increase HICP energy by 1% on impact. Controls: 6 lags for monthly and 2 lags for quarterly outcome variables, respectively, linear trend, and euro crisis dummy. The solid line is the point estimate, and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors are computed based on the lag-augmentation approach.

## 4.2. The Cross-Section of EU Households

We now turn to the second part of our money-metric welfare calculation: the cross-sectional moments of household income, expenditure, and portfolio positions. We are particularly interested in differences along education and the income distribution.

Table 1 presents summary statistics on (after-tax) labor and transfer income, major expenditure categories, housing wealth, and assets, as well as their variation across the two education groups and three income groups we consider. As expected, non-college-educated and low-income households, on average, have much lower incomes but receive relatively more in transfer income. Low-income households spend more than they earn,

Table 1: Descriptive Statistics on Households by Education and Income Groups

| | Overall | By Education Level | | By income group | | |
|---|---|---|---|---|---|---|
| | | Non-college | College | Low | Mid | High |
| **Income** | | | | | | |
| Labor income | 15,823 | 12,194 | 23,985 | 5,351 | 15,199 | 25,636 |
| Transfer Income | 876 | 936 | 718 | 1,335 | 743 | 679 |
| Pension Income | 5,383 | 5,559 | 4,927 | 3,965 | 6,025 | 5,522 |
| **Expenditure** | | | | | | |
| Housing and utilities | 5,595 | 5,320 | 6,386 | 5,116 | 5,184 | 7,483 |
| Transport | 1,979 | 1,742 | 2,660 | 1,394 | 1,906 | 3,368 |
| Goods | 4,202 | 3,988 | 4,817 | 3,814 | 3,936 | 5,588 |
| Other services | 3,238 | 2,780 | 4,555 | 2,429 | 3,072 | 5,298 |
| **Wealth** | | | | | | |
| Housing wealth | 45,830 | 43,395 | 68,035 | 24,905 | 44,652 | 84,070 |
| Other assets | 32,122 | 29,256 | 62,174 | 11,647 | 29,503 | 80,730 |
| **Household characteristics** | | | | | | |
| Age | 52 | 54 | 48 | 54 | 53 | 50 |
| Education (% with college degree) | 27.9% | 0% | 100% | 14.8% | 24.1% | 48.6% |

*Notes:* Descriptive statistics on household characteristics: Average household income and expenditure, average wealth, average age as well as the share with college degree. All monetary terms are expressed in 2015 Euros. Income and expenditure figures are annual estimates. Goods expenditures include food and beverages, alcohol and tobacco, clothing, and equipment. Other services include communication, education, health, recreation and culture, and restaurants and hotels. Age and education characteristics were taken from the EU-SILC dataset separately.

which could reflect borrowing, dis-saving, or unreported income. Relative to their total expenditures, both non-college-educated and low-income households allocate a larger share to housing and utilities. In addition, they own far less wealth than college-educated and more affluent households.

In terms of demographics, age distributions across income groups are relatively similar. However, as expected, the share of college-educated individuals is substantially lower among low-income households: only about 15%, compared to nearly 50% in the high-income group.

In Appendix Tables C.1-C.2, we provide further descriptive statistics by region and age. The wealthiest region is the West, followed by Northern, Southern, and then Eastern European countries. Interestingly, Eastern European countries spend a smaller share of their income on energy-intensive goods such as housing and utilities, and transport.

## 5. Money-metric Welfare Calculations

We now report the welfare cost of carbon-policy shock calculations. We construct the money-metric utility losses associated with the carbon policy shocks: the data counterpart of (1). We group households along three dimensions: age, education, and income. For the age groups, we consider 25-34, 35-49, 50-64, and over 65. Throughout, we evaluate the welfare consequences of a carbon policy shock that increases HICP energy by 1% on impact. We limit our focus to short- to medium-run impacts over a three-year horizon, as we lose statistical power if we estimate the effects further out. The welfare changes are expressed as a share of total three-year consumption. We only report 68% confidence bands given the short sample and considerable estimation uncertainty regarding the responses used in the welfare calculations.

Table 2: Average Welfare Loss

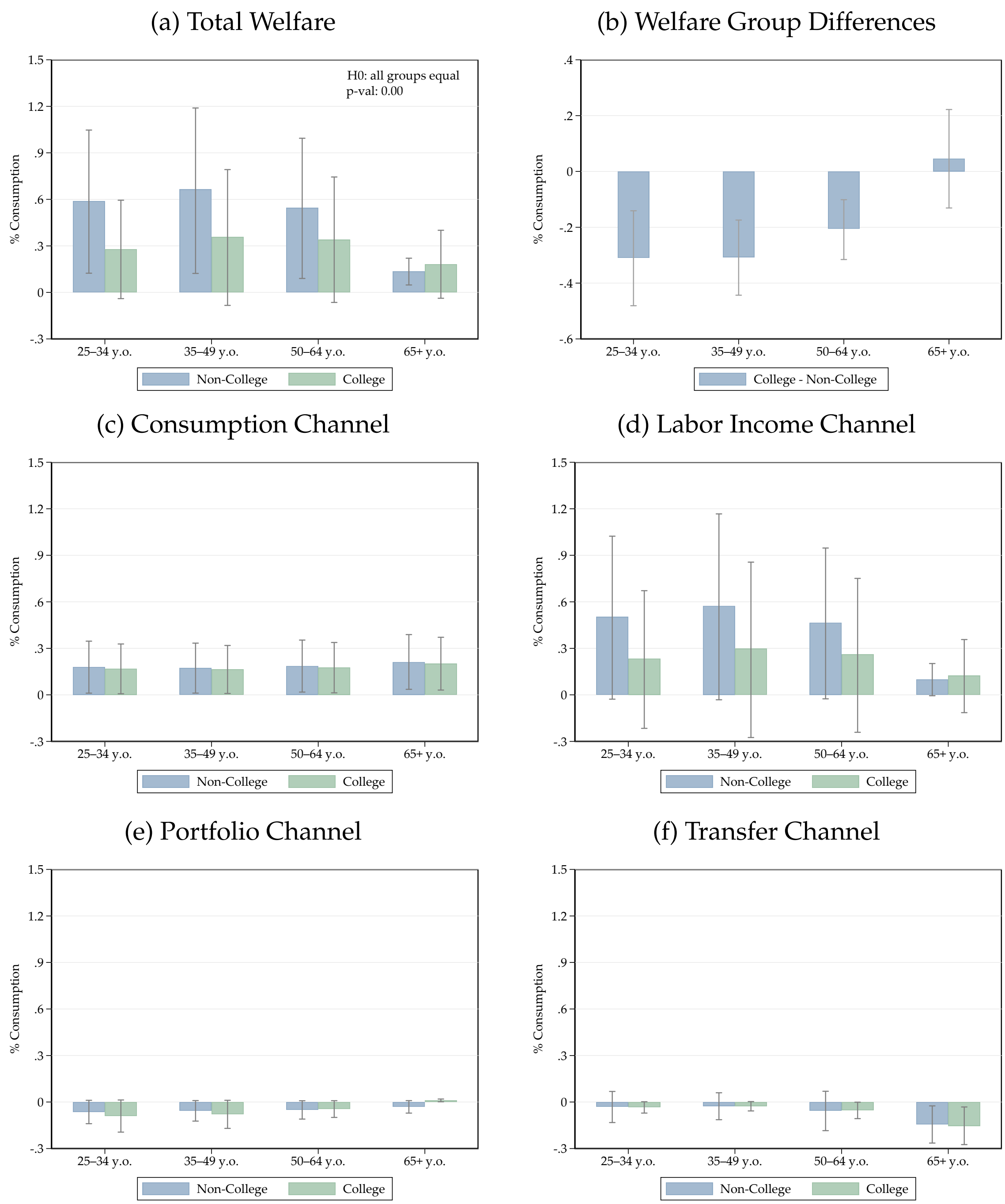
| | Total Welfare | Consumption | Labor Income | Portfolio | Transfer Income |
|---|---|---|---|---|---|
| Loss (%) | 0.51 | 0.19 | 0.43 | -0.04 | -0.07 |
| | [0.06, 0.94] | [0.02, 0.35] | [-0.08, 0.93] | [-0.10, 0.01] | [-0.15, 0.02] |

*Notes:* Money-metric welfare impacts, estimated based on (1). We compute welfare changes by age group and weight them by population shares to obtain the average effect. The welfare change is expressed as a share of total three-year consumption based on 2015 data. Positive values indicate welfare losses, while negative values indicate welfare gains. We present 68% bootstrapped confidence bands.

The average household experiences a substantial welfare impact: a carbon policy shock that increases energy prices by 1% leads to a welfare loss of about 250 euros. This translates into a loss of around 0.5% in terms of three-year consumption. From Table 2, we can see that the labor income and consumption channels drive the aggregate effect. The estimates, however, mask considerable uncertainty, with the 68% confidence bands for the total effect ranging from 0.06% to 0.94%.

**Heterogeneity by education.** How do the welfare effects vary by different groups of households? We start by studying how the welfare costs differ by educational attainment. Figure 7 presents the results. The top panels show the total welfare loss for different education and age groups, together with the corresponding welfare group differences. Two main findings stand out: First, households without a college degree display substantially higher losses, around 0.6%, compared to 0.3% for the college-educated. Second, this pattern holds across all ages, except among the retired. Indeed, for households over 65 years old, we find much smaller welfare losses of around 0.15%.

Figure 7: Welfare Loss by Education




*Notes:* Money-metric welfare impacts, estimated based on (1), by age and education groups. The welfare change is expressed as a share of total three-year consumption by age and group based on 2015 data. Positive values indicate welfare losses, while negative values indicate welfare gains. We present 68% bootstrapped confidence bands. The welfare group differences are calculated as the difference between college-educated and non-college-educated households.

Thus, while older households have been largely responsible for climate change, they are the least affected by climate change mitigation policies. On the other hand, they also benefit the least from such policies, as the benefits will only materialize relatively far in the future.

While the losses for non-college-educated households are statistically significant at the 68% level, those for college-educated households are not statistically different from zero. However, the difference in welfare impacts across education groups is significant, as shown in the top right panel. We also conduct an F-test of the joint null that welfare effects are equal across all education and age groups.[10] This hypothesis is strongly rejected, with a p-value of 0.00.

Next, we decompose these losses into the channels operating through different parts of the budget constraint. The lower panels in Figure 7 show how the consumption, labor income, portfolio, and transfer income channels contribute to these welfare losses. The main insights are: First, there is no substantial heterogeneity in the consumption channel. Non-college-educated and older households experience the most significant decline in their share of consumption. However, the differences are minimal. The effects also turn out to be relatively modest, clustering around 0.2%. This is consistent with the fact that the energy-intensive portion of households' consumption basket is not high and does not vary substantially across households.

The results for the labor income channel are vastly different. We observe stark heterogeneity in the welfare losses through labor income, with the non-college-educated households displaying substantially larger losses (around 0.5-0.6%) compared to college-educated (below 0.3%). As expected, we only observe modest impacts for households aged 65 years or older, as most of this group is retired from the labor market.

The portfolio channel, on the other hand, leads to broad-based welfare gains. These are most pronounced among younger college-educated households. The magnitude of this channel is, however, much smaller, with average welfare gains of around 0.04%. Older households gain less or may even lose through the portfolio channel, as they are more likely to be net sellers of assets rather than buyers.

The transfer income channel also leads to welfare gains. Interestingly, we do not find large differences across different levels of educational attainment. The transfer channel is most pronounced for older households, mainly because rents are indexed to inflation in many European countries and, thus, increase with the inflationary pressure.

[10] We implement this as follows. Based on the bootstrapped distribution, we construct the variance-covariance matrix of the welfare impacts and compute the F-statistic for the joint null hypothesis that all groups experience the same welfare impact. To obtain a p-value, we compare the observed test statistic to its empirical distribution under the null, constructed from the bootstrap.

**Heterogeneity by income.** While education is a common proxy for lifetime income, it does not correlate perfectly. Hence, we also study how the effects on welfare vary by income.

Figure 8 presents the results. The top panels show the total welfare loss for different income and age groups, together with the corresponding welfare group differences. Carbon taxes lead to an increase in inequality. The most affected households are poor and young households that display significant welfare losses exceeding 1%. Interestingly, high-income households also experience significant losses. The middle-income and older households are more shielded from carbon policy shocks. Thus, unexpectedly, welfare losses by income are U-shaped.

The top right panel shows that these group differences are statistically significant at the 68% level. An F-test of the joint null that welfare effects are equal across all income and age groups yields a p-value of 0.00, providing further evidence for heterogeneous welfare impacts.

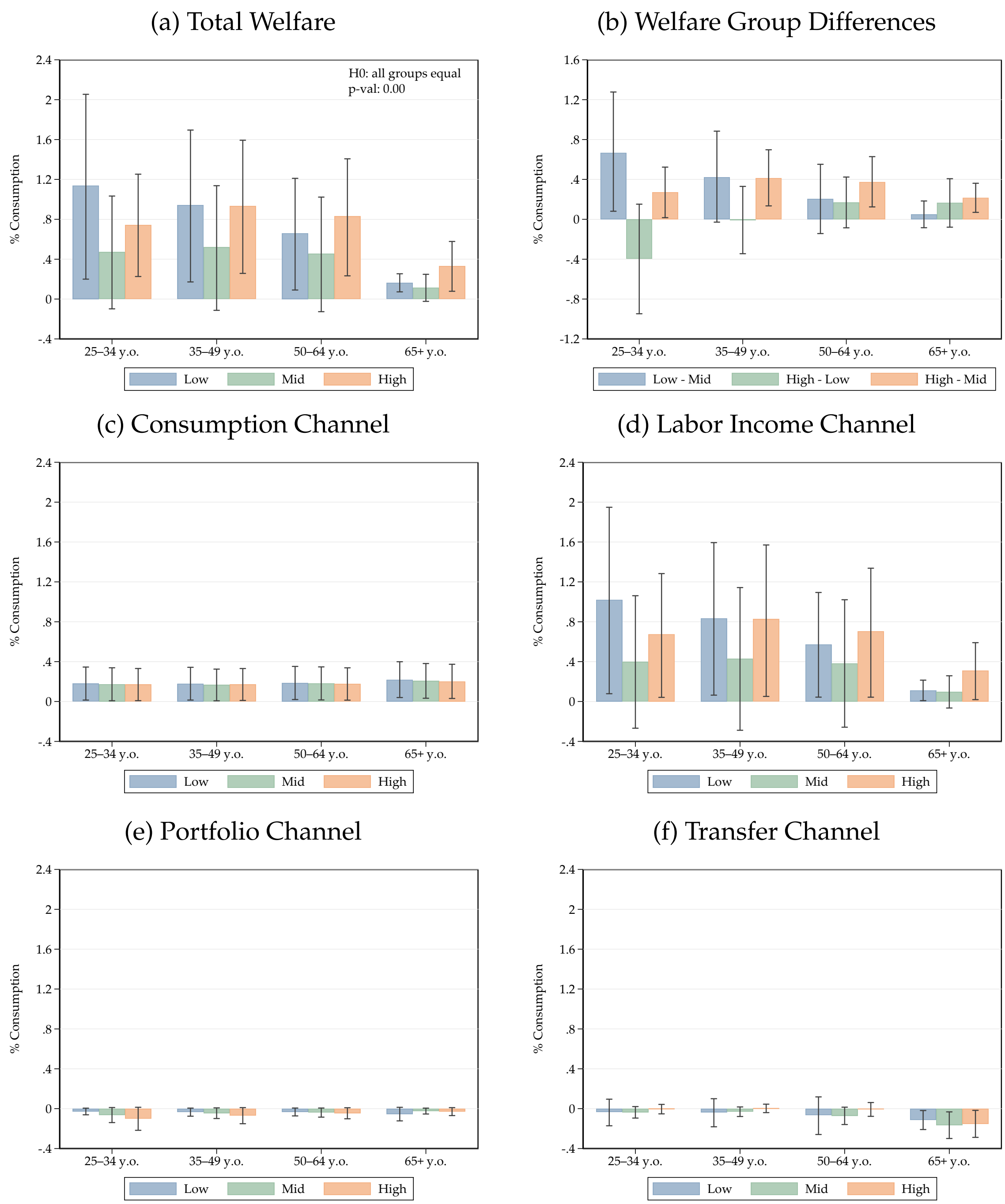
By dividing the total effect into different welfare channels, we confirm that the heterogeneity in impact is primarily due to the labor income channel, with an average effect of close to 0.5%. Importantly, these effects are considerably larger than what Del Canto et al. (2025) estimate for oil price shocks in the United States, who find around a 0.3% welfare loss from the labor income channel following a 10% oil price shock. One explanation is that labor markets are more rigid in Europe (Blanchard and Wolfers, 2000), leading to worse labor market outcomes in response to shocks. Another explanation could be that oil has become a less important input in the US economy in recent decades, whereas the EU carbon tax is levied on a broader set of energy inputs (e.g., coal and natural gas, which are inputs to electricity supply).

The portfolio channel again cushions some of these losses, particularly for high-income and younger households, but is quantitatively much less important than the labor income or the consumption channel.

**Regional heterogeneity.** We have documented substantial heterogeneity by education and income. Another important dimension is regional heterogeneity. Thus, we examine how the welfare impacts of carbon policy shocks differ across four European regions: Southern, Western, Northern, and Eastern Europe.[11] Because our main sample of euro area countries includes only a few Eastern European countries, we extend the analysis where possible to include all EU-27 countries. This allows for a more comprehensive

[11] We group European countries into these four regions according to the UN geoscheme.

Figure 8: Welfare Loss by Income




*Notes:* Money-metric welfare impacts, estimated based on (1), by age and income groups. The welfare change is expressed as a share of total three-year consumption by age and group based on 2015 data. Positive values indicate welfare losses, while negative values indicate welfare gains. We present 68% bootstrapped confidence bands. The welfare group differences are calculated as the difference between different income groups.

assessment of regional differences. However, the balance sheet data is only available for countries in the euro area. Thus, we assume that the balance sheet positions of euro-area countries within each region broadly represent all countries in that region.

Figure 9 presents the results. The top panels show the total welfare loss for different regions by age groups, together with the corresponding welfare group differences. We observe stark regional heterogeneity. The most-affected region is Southern Europe, where the welfare impact ranges between 0.5% to 0.8% for the working-age population. The welfare losses are also substantial in Eastern Europe, and to a somewhat lesser extent in Western Europe, standing at around 0.2% to 0.3%. The most insulated region appears to be Northern Europe, which displays welfare losses below 0.2%.

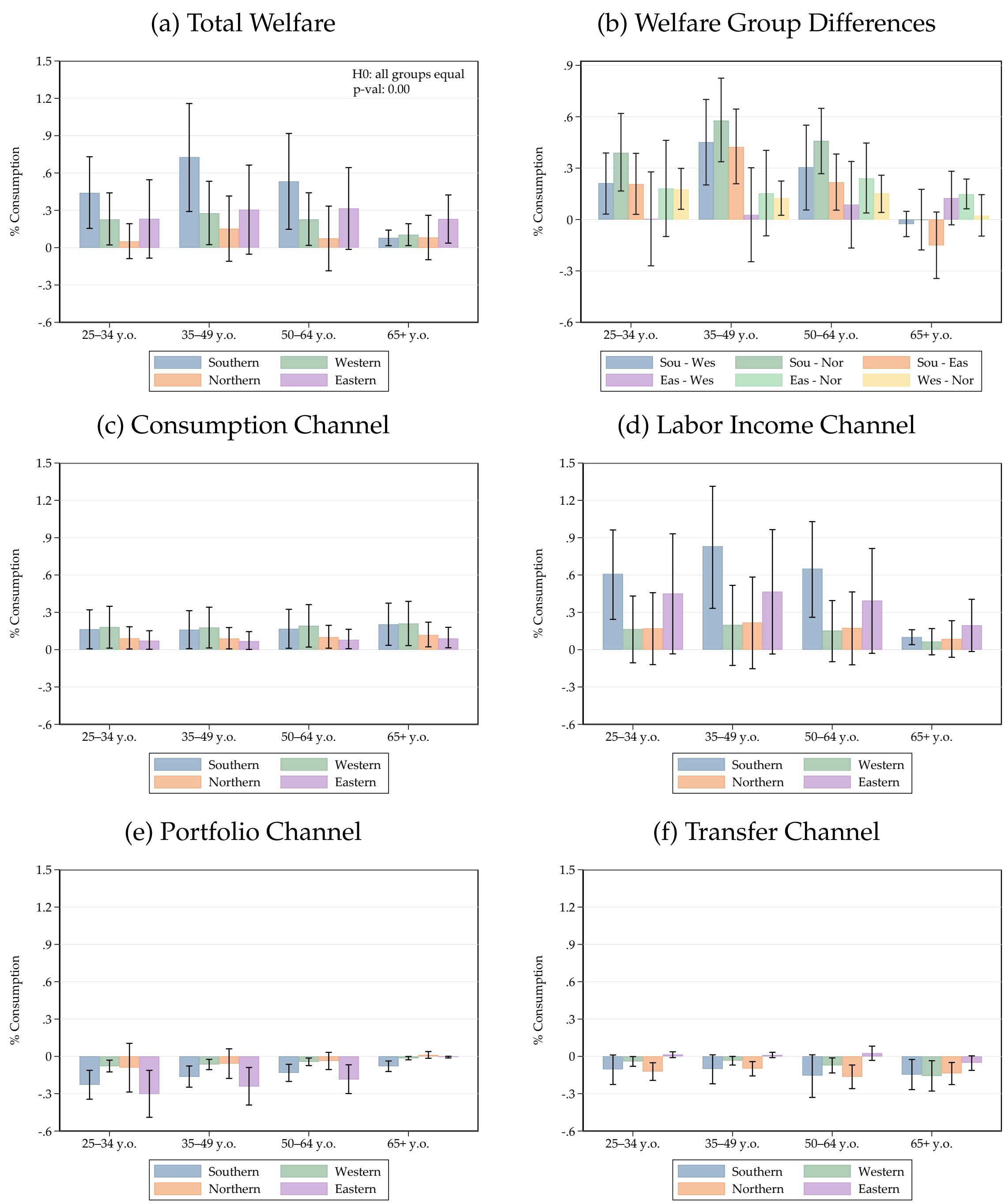
Only Southern and Western European countries display statistically significant welfare losses across all age groups. The welfare losses in Eastern Europe are only significant for the oldest age group. By contrast, the losses for Northern Europe are not statistically significant. From the top right panel, we can see that the welfare group differences are statistically significant in most cases—at least when focusing on the three younger age groups. Only the difference between Western and Eastern Europe is not statistically significant. The joint null that welfare effects are equal across all regions and age groups is again strongly rejected by the data.

Unpacking the sources of these welfare impacts, we again find a stark heterogeneity in all the channels: Southern and Western European countries display a high welfare cost through the consumption channel, standing at around 0.2%. The effect is much weaker for Northern and Eastern European countries. This is mainly driven by a lower pass-through of carbon to energy prices in these countries. Northern European countries are more insulated because they source a large share of their energy through renewables. Eastern Europe, on the other hand, was allocated a disproportionate share of free ETS allowances over our sample, which could help explain the limited price impact in that region. This is consistent with the results in Känzig and Konradt (2024).

The labor-income channel represents the largest share of losses, particularly in Southern and Eastern European countries. The effect is most pronounced in Southern Europe, consistent with the notion that labor markets in this region are more rigid due to stronger employment protection laws and less flexible wage-setting institutions. Both of these regions benefit disproportionately from the portfolio channel, but not enough to offset the impacts on consumption and labor income.

Another interesting finding concerns the impact of the transfer channel: We observe welfare gains through the transfer channel in most regions, particularly in Northern and Southern Europe. This pattern is consistent with the fact that these regions have relatively

Figure 9: Welfare Loss by Regions




*Notes:* Money-metric welfare impacts, estimated based on (1), by age and region. The welfare change is expressed as a share of total three-year consumption by age and group based on 2015 data. Positive values indicate welfare losses, while negative values indicate welfare gains. We present 68% bootstrapped confidence bands. The welfare group differences are calculated as the difference between different regions.

more generous welfare programs. In contrast, the transfer channel is absent in Eastern Europe, at least among the working-age population. This could be attributed to a generally lower level of social protection and weaker automatic stabilizers in Eastern European countries, where transfer systems are less extensive, and less effective in ameloriating economic shocks.

# 6. Conclusion

It is a curse of economics that the importance of a question is often inversely related to the precision with which it can be answered. Here, we attempt to answer an important question: the distributional impact of carbon taxes. Given its importance, the answers need further refinement. Improving data collection and understanding the budget constraints of different consumers better is one possible way forward. Another promising route is to consider higher-order effects on welfare beyond those studied here: effects on unemployment hazards or borrowing costs induced by carbon taxes.

Despite the many limitations, the estimates here, especially in light of corroborating survey evidence, offer insights into reducing opposition to carbon taxation. We highlight three takeaways:

1. The sizable welfare losses suggest that public resistance may stem from genuine economic concerns, not simply distrust of taxes or an ideological divide. On average, an increase in carbon taxes that raises energy prices 1% causes a $\approx 0.5\%$ decrease in money-metric welfare as a fraction of three-year consumption.

2. Because the main driver is indirect macroeconomic feedback through the labor income channel, measures beyond conventional public finance approaches—such as compensation schemes that focus solely on prices—may be beneficial. For example, the results suggest that expansionary (green) monetary policy could help ease the income burden, though perhaps at some inflationary cost.

3. The disproportionate burden on working-age households relative to retirees highlights the right direction of targeted redistribution: from the old to the young.

We hope this exercise inspires complementary research, leading to a shared consensus. Such consensus is essential for formulating a more comprehensive climate-change policy, one that also accounts for distributional impacts.

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# Online Appendix

## Carbon Pricing and Inequality: A Normative Perspective

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## Contents

# A. Framework

This framework follows the work of Del Canto et al. (2025), interested readers should refer to that paper for more detail. Time is discrete and indexed by $t$. There is a continuum of households indexed by $i$. There is both aggregate and idiosyncratic uncertainty; let $s_t$ denote a history of realizations of states of the world, including idiosyncratic states, up to period $t$. We will call this history a state for convenience, but it should be read to include a sequence for previous realizations of stochastic variables before $t$. There are $J$ consumption goods, indexed by $j \in \{1, \ldots, J\}$, with good $j$ having price $p_{jt}(s_t)$ in period $t$.

There are $K + 1$ long-lived assets, indexed by $k \in \{0, 1, \ldots, K\}$, available for trading in each period. Asset $k$ pays a nominal dividend $D_{kt}(s_t)$ and may be traded at a price $Q_{kt}(s_t)$ in state $s_t$. We assume that asset $k = 0$ is a one-period nominal bond which pays one unit in all states $s_t$. We define the cumulative return on buying a sequence of these bonds from period 0 to $t$ as $R_{0\to t}(s_t) \equiv \prod_0^{t-1} Q_\tau(s_\tau)^{-1}$ . Lastly, asset $k = 1$, which we term "money", serves as the numeraire in this economy, pays a zero dividend forever, and is completely durable.

The economy is populated by a finite set of $G$ different household types with overlapping generations. Let $a$ denote the age of a household at some reference time $t = 0$, which we call the household's "initial age". A household type is determined by a combination of their initial age $a$ and their group $g$. They die at group- and age-dependent rates, and we denote the cumulative survival rate of a cohort of initial age $a$ by time $t$ as $\delta_t^{ag}$. Note that this nests both the canonical infinitely lived household with $\delta_t^{ag} = 1$, constant death rates, and finitely-lived overlapping generations structures with realistic death probabilities.

Let $N_{kt}^{ag}(s_t)$ denote the amount of asset $k$ held by group $g$ of initial age $a$ at time $t$ given a realization of $s_t$, where a negative value for $N_{kt}^{ag}$ represents borrowing. We let $\Delta$ represent the first-difference operator so that $\Delta X_t^{ag} \equiv X_t^{ag} - X_{t-1}^{ag}$. Assets are subject to convex adjustment costs $\chi_k^{ag}(\Delta N_{kt})$. The one-period bond is assumed to not be subject to adjustment costs.

Let $T_t^{ag}(s_t)$ denote government transfers (or taxes, if negative) to households of group $g$ and initial age $a$ in period $t$ given a realization of $s_t$.

Households have time-separable preferences with subjective discount factor $\beta_t^{ag} \in (0, 1)$. This is read as a household of initial age $a$, in group $g$, discounting period $t$ from period zero, where the rate at which they discount is potentially non-constant. The household has preferences over consumption, labor, and asset holdings. We assume that each household type derives utility from consumption via an aggregator of goods

$$C_t^{ag} = \mathcal{C}_t^{ag}(\{c_{jt}^{ag}\}_{j=1}^J), \tag{1}$$

where $c_{jt}^{ag}$ is the consumption of good $j$ chosen in period $t$ by household $g$ that is of initial age $a$. We assume that $\mathcal{C}_t^{ag}(\cdot)$ is increasing and continuously differentiable in all its arguments.

Households of type $ag$'s preferences may be summarized by the differentiable utility function
$U^{ag}(C_t^{ag}, \{N_{kt}^{ag}\}_{k=1}^K, L_t^{ag})$, where $L_t^{ag}$ is the labor supplied by households of initial age $a$ at time $t$. We assume that $U^{ag}(\cdot)$ is weakly increasing and concave in its first two arguments, and weakly decreasing and convex in labor. Note we assume that bonds do not enter the utility function, but money or other assets might. Excluding the quantity of one-period bonds from being in the utility function directly allows us to conveniently characterize an Euler equation for the households in terms of expected marginal utilities of consumption and the return on the bond.

Labor income for individual $i$ is given by the product of three terms: $W_t^{ag}(s_t)e_t^i(s_t)L_t^{ag}(s_t)$. $W_t^{ag}$ is an aggregate component of wages that varies with the aggregate state of the economy, as well as the age and group of the individual. $e_t^i(s_t)$ is an idiosyncratic stochastic process for efficiency units of labor, which has support on $\mathbb{R}_+$ and satisfies $\mathbb{E}_0[e_t^i] = 1$. This captures both general transitory and permanent fluctuations to idiosyncratic labor income. The stochastic process for $e_t^i$ may be different for different household groups $g$ and initial ages $a$. The state $s_t$ contains realizations of both aggregate and idiosyncratic processes. We assume aggregate and idiosyncratic risks are independent so that we can partition the state into an aggregate component, $s_t^A$, and an individual component $s_t^i$: $s_t = \{s_t^A, s_t^i\}$ and $\pi_t(s_t) = \pi_t(s_t^A)\pi_t(s_t^i)$.

A representative type $g$ household of initial age $a$ takes as given its initial stock of asset holdings $\{N_{k,-1}\}_k$ and is a price taker. It solves the following utility-maximization problem:

$$V^{ag}(\{N_{k,-1}\}_k) = \max_{\{\{c_{jt}^{ag}(s_t)\}_j, L_t^{ag}(s_t), \{N_{kt}^{ag}(s_t)\}_k\}_{t=0,s}^{\infty}} \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta_t^{ag}\delta_t^{ag} U^{ag}(C_t^{ag}(s_t), \{N_{kt}^{ag}(s_t)\}_{k=1}^K, L_t^{ag}(s_t)), \tag{2}$$

subject to state-by-state budget constraints for all $t$,

$$\sum_j p_{jt}(s_t)c^{ag}_{jt}(s_t) = \sum_k \left[N^{ag}_{kt-1}D_{kt}(s_t) - Q_{kt}(s_t)(\Delta N^{ag}_{kt}(s_t)) - \chi^{ag}_k(\Delta N^{ag}_{k,t}(s_t))\right] \\ + W^{ag}_t(s_t)e^i_t(s_t)L^{ag}_t(s_t) + T^{ag}_t(s_t),$$

the consumption aggregator (1), and a series of no-Ponzi conditions

$$\lim_{T\to\infty} \mathbb{E}_0[R^{-1}_{0\to T}N^{ag}_{kT}Q_{kT}] \geq 0, \qquad \forall k \in \{0,\dots,K\}. \tag{3}$$

**Stochastic Structure**. We suppose that the (general equilibrium) law of motion for the prices of the economy admits a VAR representation. Concretely, we assume that dividends, asset prices, goods prices, wages, and transfers are stochastic, and take the form

$$D_{kt} = \bar{D}_{kt}\exp(v^D_{kt})^\sigma, \qquad Q_{kt} = \bar{Q}_{kt}\exp(v^Q_{kt})^\sigma, \qquad p_{jt} = \bar{p}_{jt}\exp(v^p_{jt})^\sigma, \\ W^{ag}_t = \bar{W}^{ag}_t\exp(v^{W^{ag}}_t)^\sigma, \qquad T^{ag}_t = \bar{T}^{ag}_t\exp(v^{T^{ag}}_t)^\sigma, \tag{4}$$

where $\sigma > 0$ is a parameter that scales the variance of the aggregate stochastic processes. These variables depend on a deterministic time component, denoted with a bar (e.g. $\bar{D}_{kt}$), and a stationary shock process (e.g. $v^D_{kt}$). We assume that the shock processes are functions of current and lagged values of a structural shock vector $\boldsymbol{\epsilon}_t$, such that

$$v^D_{kt} = \theta^D_k(L)\boldsymbol{\epsilon}_t, \qquad v^Q_{kt} = \theta^Q_k(L)\boldsymbol{\epsilon}_t, \qquad v^p_{jt} = \theta^p_j(L)\boldsymbol{\epsilon}_t, \\ v^{W^{ag}}_t = \theta^{W^{ag}}(L)\boldsymbol{\epsilon}_t, \qquad v^{T^{ag}}_t = \theta^{T^{ag}}(L)\boldsymbol{\epsilon}_t,$$

where each $\theta(L)$ is a lag operator matrix of finite dimension, and the elements of $\boldsymbol{\epsilon}_t$ are mutually uncorrelated. We collect these $v^x_t$ into a vector $\mathbf{v}_t$. We further assume that the structural shocks $\mathbf{v}_t$ have no direct effect on household utility functions; we therefore rule out preference shocks, such as discount rate shocks. Finally, we assume that these structural aggregate shocks are independent from the idiosyncratic income process for each individual.

We leave the production structure of the economy unspecified, as long as equilibrium can be written in this fashion. Importantly, the aggregate economy need not be efficient.

Following Stock and Watson (2018), we define the vector of structural impulse responses of the collection of variables affecting households' budget constraint

$$\mathbf{v}_t \equiv (\{v^p_{jt}\}_j, \{v^Q_{kt}, v^D_{kt}\}_k, \{v^{W^{ag}}_t, v^{T^{ag}}_t\}_{ag})$$

at time $t$ to the $n^{th}$ entry of the structural shock vector $\boldsymbol{\epsilon}$ at time $t = 0$ as

$$\boldsymbol{\Psi}_{n,t} \equiv \mathbb{E}_0[\mathbf{v}_t|\epsilon^n_0 = 1] - \mathbb{E}_0[\mathbf{v}_t|\epsilon^n_0 = 0].$$

Elements of this vector are denoted with superscripts, such as $\Psi^{p,j}_{n,t}$ for the consumption price of good $j$, and $\Psi^{Q,k}_{n,t}$ for the asset price of asset $k$.

## A.1. Accounting for Idiosyncratic Risk

If the noise facing households on their idiosyncratic labor endowment $e^i_t(s_t)$ does not become small, a similar formula may be derived to equation (1) in the main text. Let $U_C(s_t)$ denote the marginal utility of the consumption under the household's optimal choices after realization of history $s_t$. Now define the shifter

$$\Theta^W_t \equiv Cov\left(\frac{U_C(s_t)/P_t(s_t)}{\mathbb{E}_0[U_C/P_t]}, \frac{W_t(s_t)e(s_t)L_t(s_t)}{\mathbb{E}_0[W_t e_t L_t]}\right).$$

This captures how deviations of marginal utility from the mean move with (de-meaned) labor income. When markets are complete and aggregate risk is absent, households perfectly smooth consumption, and so this covariance is zero. With uninsurable labor-income risk and risk-averse preferences, these $\Theta^W_t$ will generally be negative. Similarly, define

$$\Theta^{p,j}_t \equiv Cov\left(\frac{U_C(s_t)/P_t(s_t)}{\mathbb{E}_0[U_C/P_t]}, \frac{p_{j,t}(s_t)c_{jt}(s_t)}{\mathbb{E}_0[p_{j,t}c_{jt}]}\right) \qquad \Theta^T_t \equiv Cov\left(\frac{U_C(s_t)/P_t(s_t)}{\mathbb{E}_0[U_C/P_t]}, \frac{T_t(s_t)}{\mathbb{E}_0[T_t]}\right)$$

$$\Theta^{D,k}_t \equiv Cov\left(\frac{U_C(s_t)/P_t(s_t)}{\mathbb{E}_0[U_C/P_t]}, \frac{D_{kt}(s_t)N_{kt-1}(s_{t-1})}{\mathbb{E}_0[D_{kt}N_{kt-1}]}\right) \qquad \Theta^{Q,k}_t \equiv Cov\left(\frac{U_C(s_t)/P_t(s_t)}{\mathbb{E}_0[U_C/P_t]}, \frac{Q_{kt}(s_t)\Delta N_{kt}(s_t)}{\mathbb{E}_0[Q_{kt}\Delta N_{kt}]}\right)$$

as the covariance of (detrended) marginal utility of consumption with (detrended) good expenditures, asset holdings, asset expenditures, and transfers.

These covariance weights tend to be negative. Particularly for labor income: in states when the household has unexpectedly high income, and they are not perfectly smoothing due to borrowing constraints or incomplete markets, their marginal utility of consumption tends to be low. As such, including adjustments for idiosyncratic risk into the formula tends to lower somewhat the welfare costs of a shock, as it discounts the price movements more heavily.

**Proposition 1.** *As only aggregate risk becomes small ($\sigma \to 0$), the first-order change in money-metric welfare from an impulse to an element $n$ of the fundamental shock vector at $t = 0$ is*

$$dV = \sum_t R_{0\to t}^{-1} \Bigg[ \Bigg( \underbrace{-\sum_j \mathbb{E}_0[p_{j,t} c_{jt}] \Psi_{n,t}^{p,j} (1 + \Theta_t^{p,j})}_{\text{Consumption Price Changes}} + \underbrace{\mathbb{E}_0[W_t e_t^i L_t] \Psi_{n,t}^{W} (1 + \Theta_t^{W})}_{\text{Labor Income Changes}} \tag{5}$$

$$+ \sum_k \Bigg[ \underbrace{\mathbb{E}_0[N_{kt-1} D_{kt}] \Psi_{n,t}^{D,k} (1 + \Theta_t^{D,k})}_{\text{Asset Income Changes}} - \underbrace{\mathbb{E}_0[Q_{kt} \Delta N_{kt}] \Psi_{n,t}^{Q,k} (1 + \Theta_t^{Q,k})}_{\text{Asset Price Changes}} \Bigg] + \underbrace{\mathbb{E}_0[T_t] \Psi_{n,t}^{T} (1 + \Theta_t^{T})}_{\text{Transfer Income Changes}} \Bigg) \Bigg],$$

*where choices and risk-adjustment shifters are evaluated at $\sigma = 0$.*

This formula is very similar to that found in equation (1). However, price movements are now weighted by the covariance of marginal utilites of consumption with each element of the budget set (labor income, goods expenditures etc.). Note that when idiosyncratic risk vanishes, households are risk-neutral or there are complete markets, all $\Theta_t^x$ are equal to zero, and we recover the formula in equation (1).

These covariance shifters are in principle estimable, though doing so requires consumption spending and a parametric assumption on the functional form of utility. Del Canto et al. (2025) estimate values for their sample of US households, and find them to be on the order of -0.1 to -0.4, in accordance with evidence from Krueger, Malkov, and Perri (2023). Incorporating such values here would attenuate the welfare losses by a similar magnitude, but not change the relative distributional results.

# B. Data Appendix

This appendix describes the data used in our analysis. It describes the datasets used: the Household Budget Survey (HBS), the EU statistics on income and living conditions (EU-SILC), and the Household Finance and Consumption Survey (HFCS) as well as the methodology used for cleaning the data. We also provide a description on the additional macroeconomic price data used.

## B.1. Household Budget Survey (HBS)

The Household Budget Survey is comprised of national surveys focusing mainly on household expenditure on goods and services in the EU. This contains administrative data and is provided by Eurostat. They were launched in most euro states in the 1960s.

The surveys have been conducted by Eurostat in all EU countries every 5 years, starting in 1988. The most recent waves are 2015 and 2020. This dataset contains granular information on households' expenditure at the annual level. Its main aim is to measure the consumption weights for the HICP. We use data from the 2015 wave, which is our base year.

We use the HICP 12 main components: alcoholic beverages and tobacco, clothing and footwear, communication, education, food and non-alcoholic beverages, furnishings, household equipment, health, housing and utilities, recreation and culture, restaurants and hotels, transport, and miscellaneous goods and services.

We focus on households aged 25 or older and at most 75 years old. We calculate per-capita household consumption by dividing household total consumption by household equivalent size (using the OECD scale, already provided in the survey). We group households age groups and another grouping category: education level, income group or regions. Education level is defined by the household head (already defined in the survey) and income groups are calculated as the top 25% (high), bottom 25% (low) and mid 50% (mid) using household net income. We then calculate the average expenditure for each one of these consumption categories for each group and age group. This results in the life-cycle consumption component.

We also calculate the three-year consumption profile for each group and age group. To do this, we first minimize jumps in consumption patterns caused by measurement error by running a Locally Weighted Scatterplot Smoothing (LOWESS) for each of the categories and each of the groups by age (without grouping by age groups yet). We then calculate the three-year consumption profile for a given group by assuming a constant life-cycle profile of consumption. We interpolate consumption by age for a given group and then calculate the total three-year consumption profile. We then group by age-groups and get three-year consumption profiles by each demographic group.

## B.2. EU Statistics on Income and Living Conditions (EU-SILC)

The EU-SILC collects cross-sectional and longitudinal data on income, poverty, social exclusion, and living conditions. This survey is conducted annually across the EU. This survey is used to construct both life-cycle and time-series income statistics (both labor and transfers) for specific household groups. It is available from 2004 for some countries and 2005 for most euro area countries.

We construct labor income at the household level by adding cash and non-cash employment income. We build transfers by adding regular transfers and pensions. Regular transfers contain unemployment, sickness, disability and education benefits. On the other hand, pensions contain old age and survivors benefits. We use the household head education level to group houses. The household head is not defined in the survey, so we define it as the member who earns the highest income. We group houses into income groups by using net income at the household level in a similar way as with the consumption data.

We then proceed in two steps. We first calculate the life-cycle component by taking the weighted average labor and transfer income for each demographic group in our base year—2015. As a second step, we derive annual income time series for each group—education level, income group, or region—without grouping by age to reduce noise in the impulse response functions. This allows us to study the heterogeneous effect of carbon pricing on different groups, as in Känzig (2023). These time series are built by taking the weighted averages for each group. We only calculate the time series for labor income and regular transfers. We exclude pensions, as most are indexed to inflation, and we can use the response of HICP to carbon prices to estimate the effect on pensions.

The annual income time series are then converted to a quarterly frequency using a Chow-lin methodology. We use euro area wage data from the ECB to interpolate labor income and the unemployment rate to interpolate transfer income. For regional labor income, we directly use regional wage data from the ECB. The regional wage data is estimated by taking a weighted average of country-level wages, weighted by 2015 GDP, our baseline year.

## B.3. Household Finance and Consumption Survey (HFCS)

The HFCS collects household-level data on household finances and consumption up to 2021. This is conducted every 4 years throughout the euro area by the ECB. It includes granular information related to households' balance sheet, income and consumption. We use this dataset to calculate life-cycle household portfolio.

We group assets into bonds, equities, and real estate. Bond holdings contains both government and corporate bonds. We don't separate into each type of bond holding as we don't have enough data. On the other hand, equities include mutual funds, directly held equities, and managed accounts. Finally, real estate is composed of housing and any other type of real estate. We also include adjustable-rate mortgages to estimate the effect of a change in mortgage yields caused by a carbon pricing shock. We focus on these rather than all mortgages as the yield for fixed-rate mortgages will not be affected by definition.

Similar to consumption, we also restrict attention to households of age between 25 and 75. We remove the top and bottom 1% of households by net worth. Demographic groups are built in the same way as with consumption and labor. We take the level of household head education to group households by education. We also group households by income groups using the household income level.

We are interested in both asset accumulation and asset holdings for the previous quarters. To do so, we use a similar approach to Del Canto et al. (2025). We first construct asset accumulation by interpolating asset holdings by year of age for a given demographic group. We then define asset accumulation as the difference in asset holding between age $a$ and age $a - 1/4$. Our approach assumes that the accumulation profile of assets is constant over time. Using this approach, we also get the asset holdings for the previous quarter.

## B.4. Additional Data Sources

We complement the household survey data with some aggregate price data from the ECB. In particular, we use the HICP and HICP components at the Euro level and at the country level. We also use house price indices as well as mortgage rates. We seasonally adjust HICP and house price data using the Census X11 approach.

The portfolio data is mainly sourced from Bloomberg. We use data for Eurostoxx 50 index and dividend yield to estimate the effect of carbon prices on the price of equities and their dividends. We use the ICE BofA corporate bond index to estimate the effect on bond prices.

# C. Additional Results

## C.1. Summary Statistics by Demographic Groups

Tables C.1-C.2 show descriptive statistics by region and age, respectively. When looking at regions, we can see that western and northern regions are the ones that earn and spend the most, followed by the southern region and eastern. The western region is the wealthiest while the northern and southern regions have similar wealth. The eastern region has lower income, consumption and wealth.

The data by age groups is consistent with a traditional life-cycle model. Labor income peaks has an inverse u-shape, peaking at mid age, whereas pension income peaks at old age for retirees. Consumption on housing increases by age but transportation decreases by age. Goods and services remain somewhat constant throughout the life-cycle. Finally, wealth increases throughout the life-cycle, where the proportion of housing assets increases as people age.

Table C.1: Descriptive Statistics on Households by Region

| | By Region | | | |
|---|---|---|---|---|
| | Southern | Western | Northern | Eastern |
| **Income** | | | | |
| Labor income | 9,551.62 | 21,070.77 | 15,032.54 | 5,351.38 |
| Transfer Income | 556.28 | 1,027.09 | 1,723.61 | 193.36 |
| Pension Income | 3,883.53 | 6,620.47 | 3,442.19 | 1,656.92 |
| **Expenditure** | | | | |
| Housing and utilities | 5,310.01 | 5,997.99 | 5,239.32 | 2,007.38 |
| Transport | 1,605.46 | 2,334.97 | 2,130.39 | 588.55 |
| Goods | 4,087.63 | 4,433.64 | 3,677.91 | 1,863.24 |
| Other services | 2,940.76 | 3,572.73 | 3,183.68 | 1,103.32 |
| **Wealth** | | | | |
| Housing wealth | 55,182.78 | 54,816.49 | 48,327.50 | 24,994.05 |
| Other assets | 32,976.06 | 49,240.89 | 34,990.50 | 11,279.20 |

*Notes:* Descriptive statistics on household characteristics. Average household income and expenditure, average wealth. All monetary terms are expressed in 2015 Euros. Income and expenditure figures are annual estimates. Goods expenditures includes food and beverages, alcohol and tobacco, clothing and food and equipment. Other services include communication, education, health, recreation and culture, and restaurants and hotels.

Table C.2: Descriptive Statistics on Households by Age Groups

| | Age Group | | | |
|---|---|---|---|---|
| | 25-34 y.o. | 35-49 y.o. | 50-64 y.o. | 65+ y.o. |
| **Income** | | | | |
| Labor income | 13,506.84 | 15,794.80 | 14,173.82 | 4,023.78 |
| Transfer Income | 952.99 | 802.44 | 1,346.68 | 244.66 |
| Pension Income | 788.88 | 595.69 | 2,825.53 | 14,202.86 |
| **Expenditure** | | | | |
| Housing and utilities | 4,880.41 | 4,806.89 | 5,618.42 | 6,706.17 |
| Transport | 2,353.41 | 2,073.76 | 2,201.13 | 1,493.86 |
| Goods | 3,816.62 | 3,905.89 | 4,437.15 | 4,434.65 |
| Other services | 3,440.27 | 3,217.42 | 3,323.53 | 3,087.69 |
| **Wealth** | | | | |
| Housing wealth | 18,370.69 | 34,933.33 | 55,307.09 | 68,982.82 |
| Other assets | 20,940.40 | 31,698.95 | 44,253.08 | 47,502.05 |

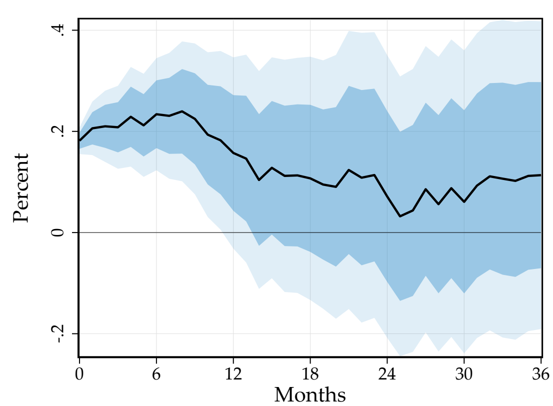
*Notes:* Descriptive statistics on household characteristics. Average household income and expenditure, average wealth. All monetary terms are expressed in 2015 Euros. Income and expenditure figures are annual estimates. Goods expenditures includes food and beverages, alcohol and tobacco, clothing and food and equipment. Other services include communication, education, health, recreation and culture, and restaurants and hotels.

## C.2. Transfer Income Channel

We divide transfer income into pension income and other transfers (e.g. government transfers). Pension income is indexed to inflation and represents a large portion of all transfer income, especially for the oldest age group. We calculate the transfer income channel by adding the change in pension and other transfer income. The change in pension income is calculated using the overall HICP impulse response function shown in Figure C.1. Inflation increases after a carbon policy shock, representing a higher pension income and a welfare gain. The welfare gain from transfer channel is more prominent for the old.

On the other hand, the change in other transfer income is calculated separately by group, similar to the labor income channel. Figure C.2 shows the other transfer income responses by education and income groups. Transfer income usually increases after a carbon shock. There is a small heterogeneity across groups. Non-college and college educated households show a similar response, although college educated households have a slightly larger response, surprisingly. However, low- and middle-income households show an increase in transfer income of similar magnitude. The main difference comes when compared to high-income households, which have a negative transfer response to a carbon policy shock, which is reflected in smaller welfare gains from transfers.

Figure C.1: HICP Response

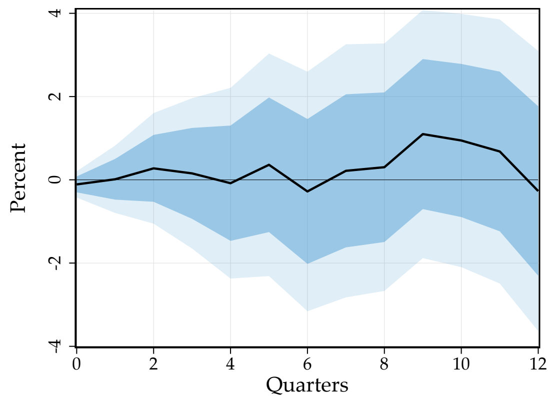



*Notes:* Impulse responses of HICP, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 2 lags of the outcome variable, linear trend and euro crisis dummy. The solid line is the point estimate and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on lag-augmentation approach.

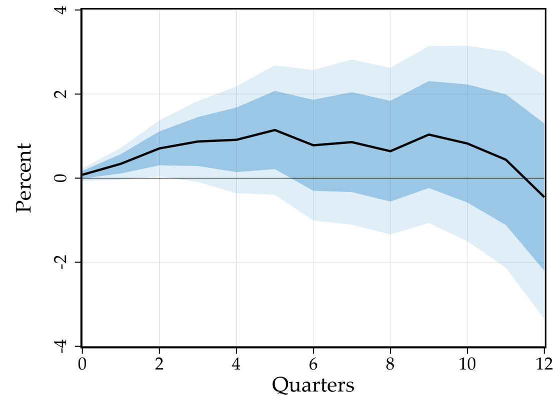
Figure C.2: Transfer Income Responses by Education and Income Groups

**Education**:

(a) Non-College Educated

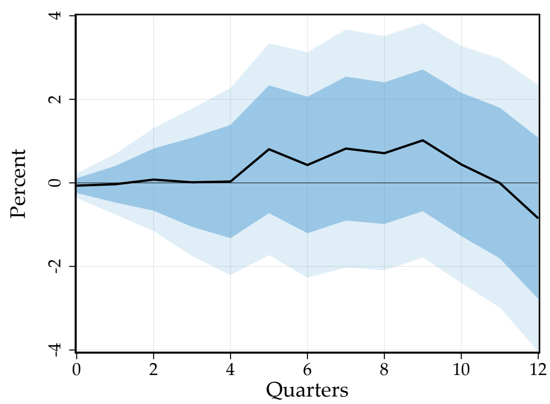



(b) College Educated

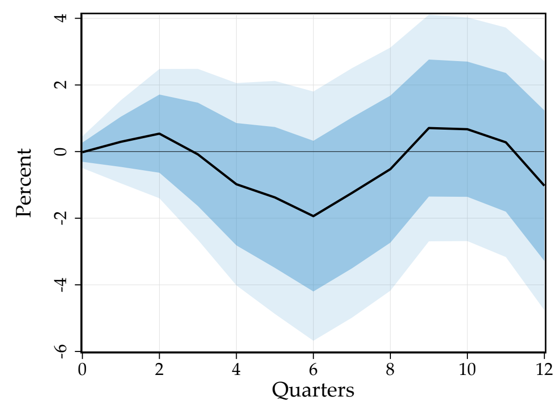



**Income**:

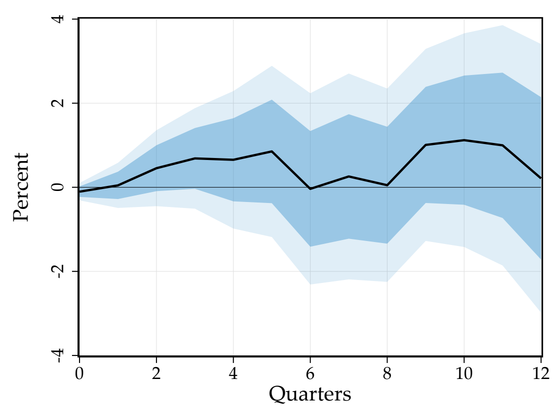
(c) Low Income




(d) High Income




(e) Mid Income




*Notes:* Impulse responses of transfer income by education and income level, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 2 lags of the outcome variable, linear trend and euro crisis dummy. The solid line is the point estimate and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on lag-augmentation approach.

## C.3. Additional Regional Responses

This section includes the impulse response functions used to calculate the regional welfare costs. We include the IRFs of HICP, labor income, transfer income, housing prices and mortgage rates.

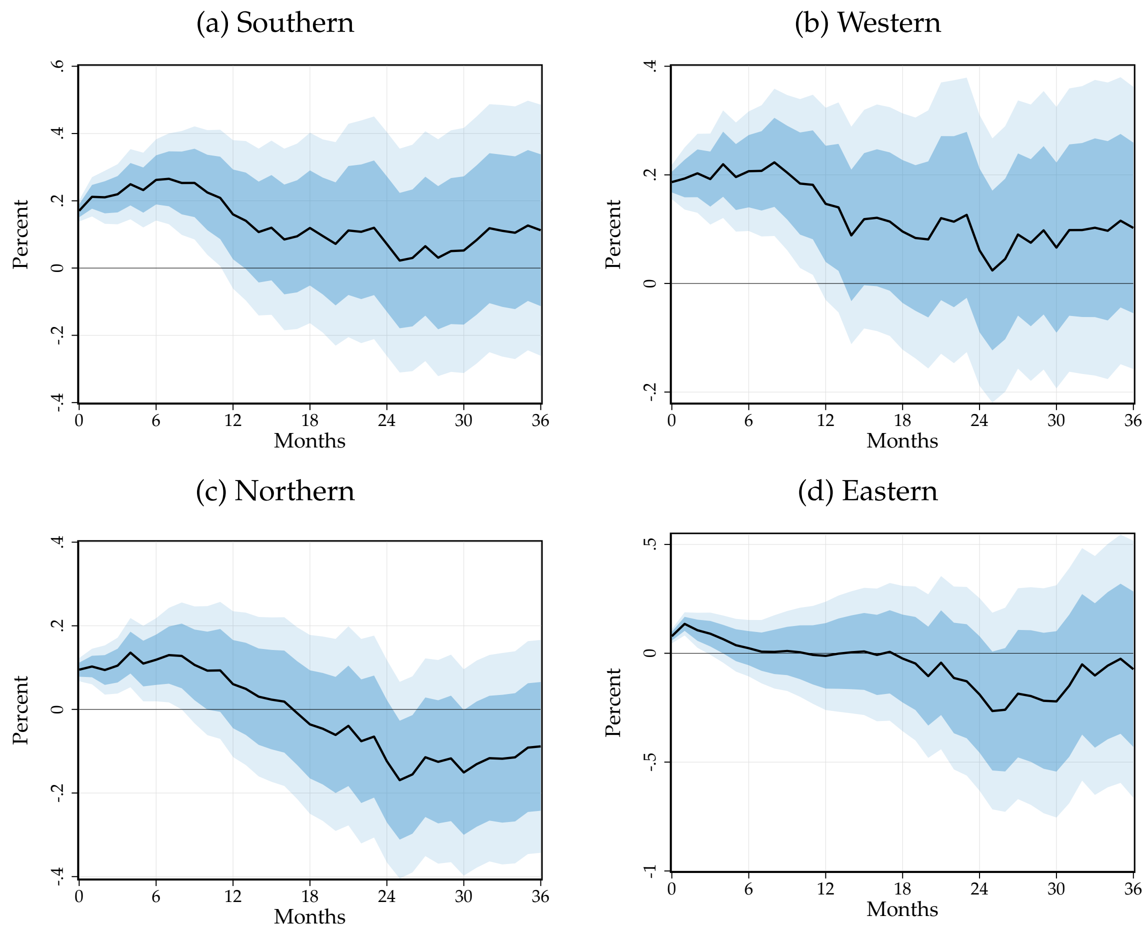
Figure C.3 shows the overall HICP response for all regions. We can see that the pass-through of EU-wide carbon policy shocks to consumer prices varies across regions, with a weaker pass-through in Northern and Eastern European countries. Note that the underlying HICP categories tend to be a bit noisy at the regional level—at least at the level of granularity we consider. Thus, to compute these responses, we scale the EU-wide HICP category responses by the pass-through at the regional level. Specifically, we divide the EU-wide HICP category response by the EU-wide overall HICP response at $h = 0$ and multiply by the regional overall HICP response at the same horizon.

Figure C.4 shows the labor income response for different regions. We can see substantial heterogeneity: This bulk of the regional heterogeneity in welfare cost documented in Section 5 comes from. We see that the southern region responds the most, followed by the eastern region. The western and northern regions have a more muted response, which is reflected in a lower welfare cost.

Figure C.5 shows the transfer income by different regions. We see the southern region has a more pronounced response, followed by the western and northern region. Interestingly, we see that the eastern region has a reduction in transfer income after a carbon policy shock—even though it is not very precisely estimated.

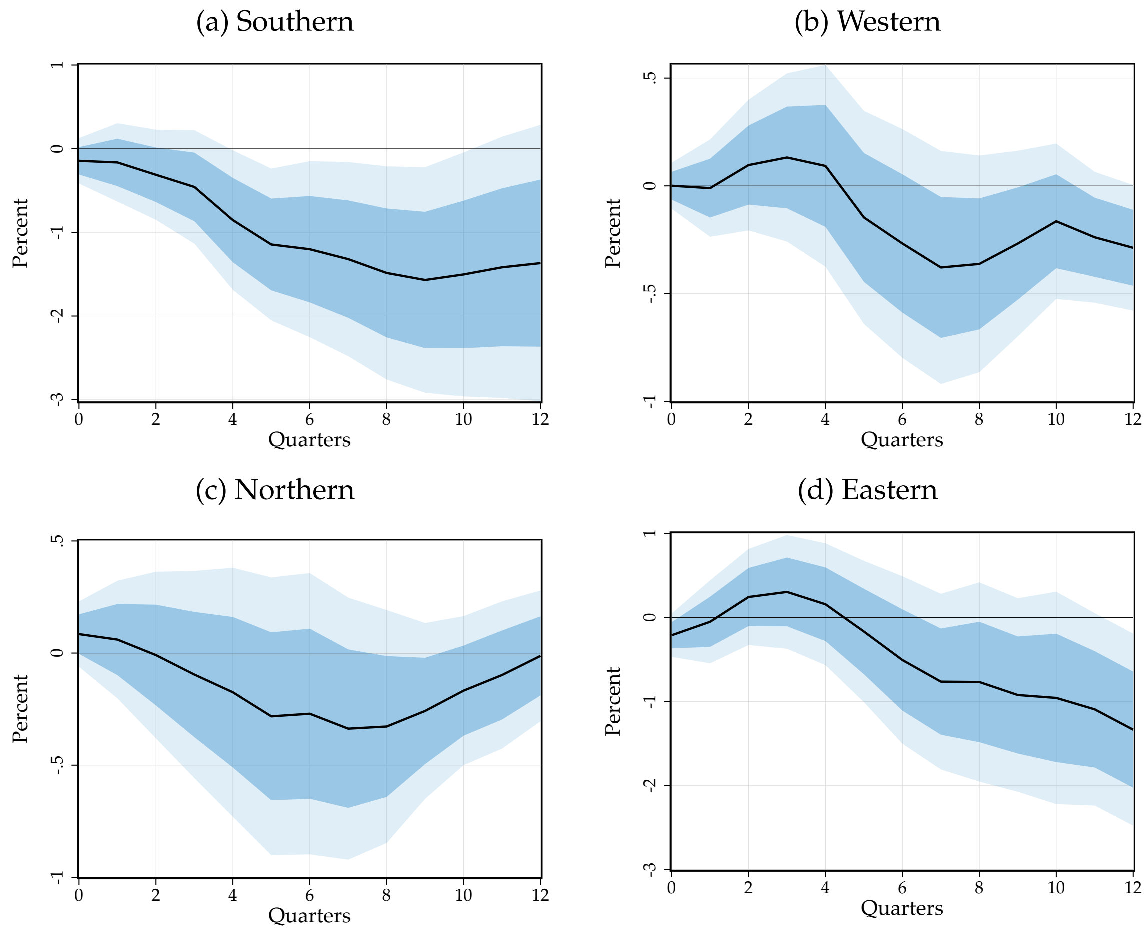
Finally, Figure C.6 shows the regional IRFs for house prices. While qualitatively similar, we see a more pronounced response for for the southern and eastern regions.

Figure C.3: HICP Response by Region



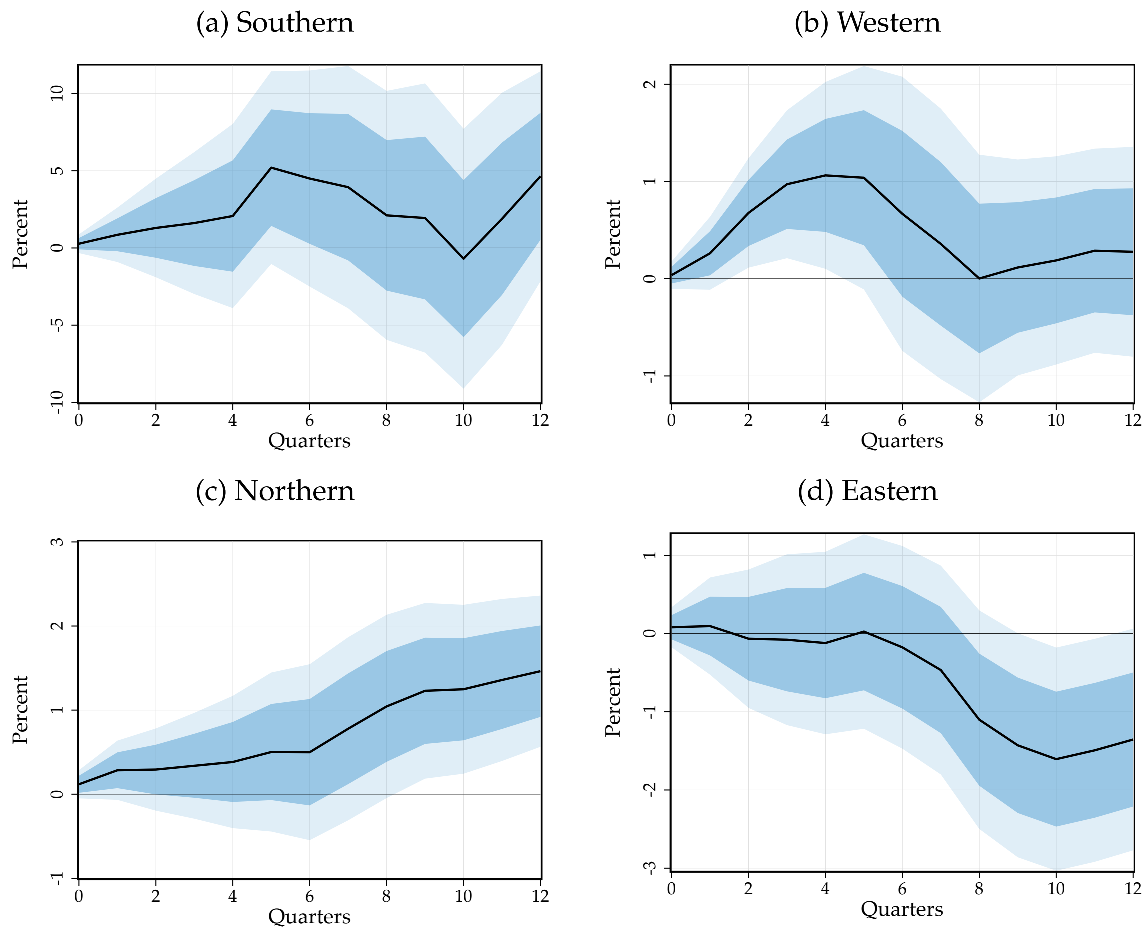

*Notes:* Impulse responses of transfer income by education and income level, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 6 lags of outcome variable, linear trend and euro crisis dummy. The solid line is the point estimate and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on lag-augmentation approach.

Figure C.4: Labor Income Response by Region



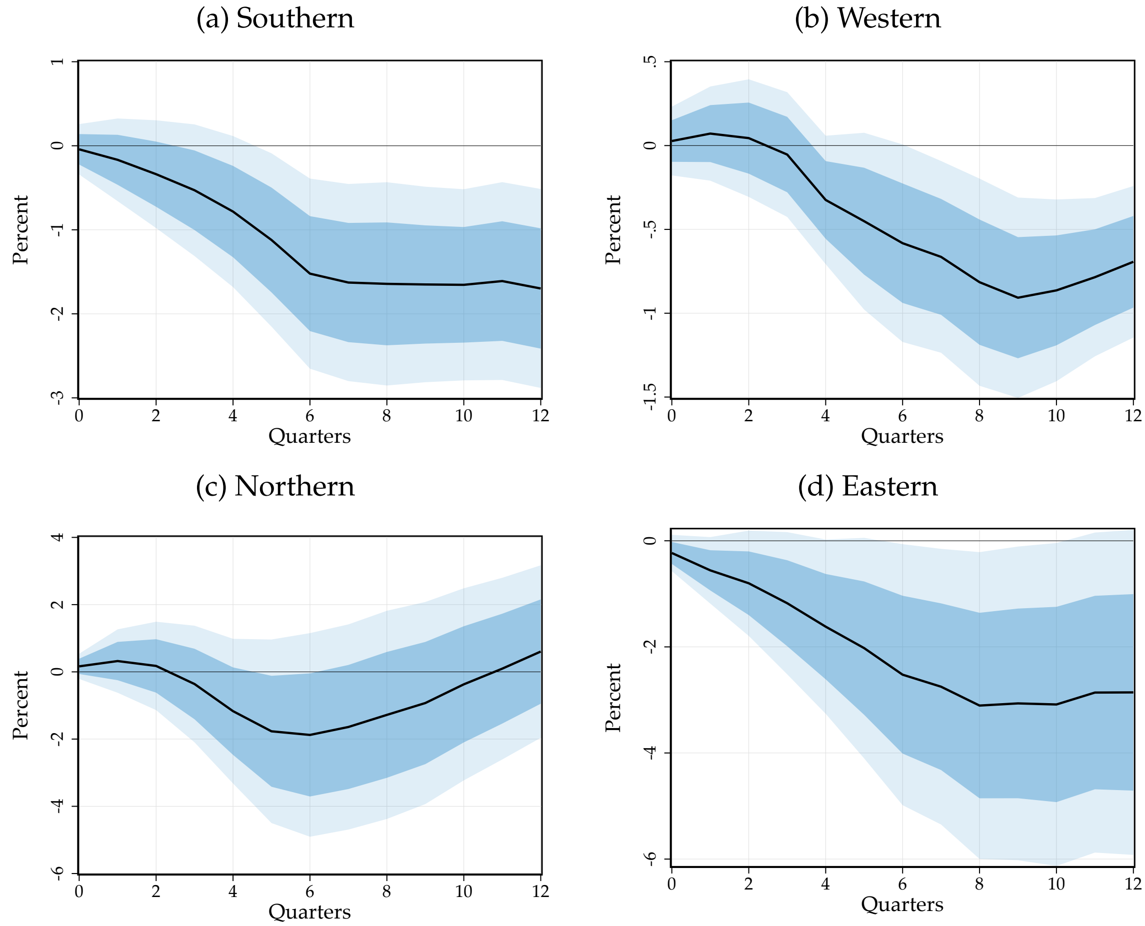

*Notes:* Impulse responses of transfer income by education and income level, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 2 lags of outcome variable, linear trend and euro crisis dummy. The solid line is the point estimate and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on lag-augmentation approach.

Figure C.5: Transfer Income Response by Region




*Notes:* Impulse responses of transfer income by education and income level, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 2 lags of outcome variable, linear trend and euro crisis dummy. The solid line is the point estimate and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on lag-augmentation approach.

Figure C.6: House Price Response by Region




*Notes:* Impulse responses of transfer income by education and income level, estimated using local projections (2) on the carbon policy shock from Känzig (2023) aggregated to quarterly frequency. The responses are normalized to increase HICP energy by 1% on impact. Controls: 2 lags of outcome variable, linear trend and euro crisis dummy. The solid line is the point estimate and the dark and light shaded areas are 68% and 90% confidence bands. Standard errors computed based on lag-augmentation approach.

# References Appendix

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