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The welfare impact of climate action: A distributional analysis for Italy

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ABSTRACT

Achieving the climate targets the European Union sets requires a complex policy mix, which is expected to cause a general increase in end-user prices, especially for carbon-intensive goods. For those countries already affected by large inequalities, this constitutes a risk of further negative impacts in distributional terms. This paper contributes to the debate by assessing the distributional impacts on Italian households of a policy mix coherent with the EU climate targets. The policy instruments considered are the removal of fossil fuels subsidies and carbon taxation. The analysis is carried out by soft-linking a dynamic CGE model with a microsimulation model at the household level. The estimation of a consumer demand system includes direct, indirect, and demand-side effects of the policy scenario. We then complement the analysis on the uses-side by simulating the impacts on the sources-side, computing the burden imposed on households by changes in the returns to production factors. The overall impacts of the climate policy lead to a welfare loss for households at all levels of the expenditure distribution. However, we find that both the uses and sources-side impacts of the policy are progressive, and the sources-side effects strongly reinforce the uses-side ones. Finally, we show that reinvesting revenues in clean energy technologies is key to improving the progressivity of climate policies in Italy.

1. Introduction

In December 2019, the European Commission launched the European Green Deal (EGD) to set the EU on the pathway to a green transition, with the ultimate goal of reaching climate neutrality by 2050. In 2021, the Fit for 55 Package was adopted to adapt existing EU climate and energy legislation to the intermediate target of a minimum 55% reduction in greenhouse gas emissions by 2030 w.r.t. 1990 levels, in accordance with the new European Climate Law. Achieving such ambitious goals will require a complex policy mix that is expected to impact energy and commodity prices in all sectors of the economy. According to the adopted instrument mix settings, the potential distributional impact on end-users can change radically.

In this work, we aim to evaluate the distributional impact of price changes related to adopting a combination of policy instruments coherent with the EU climate target in 2030 on Italian households. We focus on a policy scenario involving the joint use of a carbon tax (CT) and the phasing out of fossil fuel subsidies (FF).[1] We consider these two instruments as they are envisaged in the revision of the Energy Taxation Directive (ETD), intending to align the taxation of energy products and electricity with EU energy and climate targets. In the revision, implementing effective environmental taxation and removing incentives for fossil fuel consumption throughout the EU are explicitly mentioned as critical instruments to meeting the greenhouse gas emission reductions required by the EGD and the Fit for 55 package (EU, 2021).[2] The

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[1] We have also simulated the distributional effects of introducing a carbon tax and removing fossil fuels subsidies separately. In the first case, the carbon tax is set to achieve the emission reduction target envisaged by the Fit for 55 Package in 2030. In the second scenario, the complete subsidy removal decreases the emissions related to fossil fuel uses, endogenously reducing emissions profile which, however, is not yet compliant with the climate target for 2030. Detailed simulations for these partial scenarios are available upon request from the authors. Since results are not qualitatively different from those obtained when the two instruments are jointly implemented, we report only on results for the joint policy mix setting.

[2] Since 2009, the EU has made recurrent commitments to remove fossil fuels subsidies and encouraged other countries to do so by 2025 at the G20 and the UNFCCC. G7 (2017), G20 (2017); 2016 Clean Energy for All European package). Together with consumption subsidies, several types of direct and indirect incentives in the form of fiscal support for the production of fossil fuels through budgetary transfers and tax breaks, public lending to the sector, and capital investment by fossil fuel-related state-owned enterprises are still in place (Gencu et al., 2020).

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phasing out of fossil fuel subsidies is also urged by the 8th Environment Action Programme (EAP), which entered into force in 2022 and sets the EU common agenda for the environmental policy until 2030.[3]

Indeed, both removing fossil fuel subsidies and imposing a uniform carbon tax contribute to setting appropriate carbon pricing (IPCC, 2022). However, there is concern about the distribution of the impacts of carbon pricing across household income groups (Baranzini et al., 2017). The bulk of empirical literature focuses on the uses-side distributional effects (Koppl and Schratzenstaller, 2023), i.e., the effect on households' purchasing power stemming from the price changes induced by the policy. On the uses-side, a carbon pricing policy increasing the price of energy goods may impact households' welfare through three main channels (Pizer and Sexton, 2019). First, since low-income households spend a larger share of their budget on domestic heating and electricity, the energy price increase represents a heavier burden for them than for richer households (this is known as the *direct effect* of the price change). Second, the rise in energy prices in response to carbon pricing indirectly affects the price of other goods by changing their production costs (the so-called *indirect effects*). Third, price changes may involve behavioral reactions as, in the short run, households at different income levels may differ in their ability to change their consumption patterns in the face of price increases (these are known as *demand-side effects*). Direct, indirect, and demand-side effects may have different distributional implications, and the policy's final uses-side impact is case-specific and not *a priori* predictable. In this work, we analyze the distributional impact of the simulated policies on income uses by looking at the direct, indirect, and demand-side effects.

Another channel through which carbon pricing may affect households' welfare is on the sources of income side, by imposing burdens on the owners of production factors by changing their prices, i.e., affecting wages, returns to capital, and transfers (Fullerton, 2011; Metcalf et al., 2011). On this side, the distributional impact of carbon pricing depends on how it affects the price of different factors. Households that rely heavily on income from factors whose prices increase relative to other factor prices may be positively impacted by the policy, while the reverse happens for the owners of factors whose price decreases. We then complement our distributional analysis on the expenditure side with a simulation of the welfare impacts induced by factor price changes.

The literature has already evaluated the efficiency and effectiveness of reaching the EU targets of the policy scenario considered in this study. Antimiani et al. (2023) develop a recursive dynamic computable general equilibrium (CGE) model to analyze the contribution of the different EGD pillars to achieve the carbon neutrality target. Their results show that climate targets can be reached at the lowest cost when appropriate carbon pricing accompanies the complete phase-out of fossil fuel subsidies, and the revenues coming from the two interventions are used to foster the development of clean energy technologies through the Innovation Fund. However, this paper does not tackle the issue of the potential distributional effects of these policies. Our work complements the policy impact evaluation by further investigating the welfare burden. The simulated policies are coherent with the EU targets, while their potential distributional impacts are estimated for the expenditure and welfare of Italian consumers. Italy represents an interesting case study for several reasons. Unlike other European countries, it does not currently impose a carbon tax. Previous attempts have failed precisely due to the presumed regressivity effects on households.[4]

To perform our distributional analysis, we proceed in three steps. First, we simulate the price changes induced by the policy scenario on 36 categories of goods and services. We rely on the results from the scenario designed with the recursive dynamic CGE model adopted in Antimiani et al. (2023). This model allows us to evaluate how changes in energy prices due to the adopted policy indirectly affect the price of other commodities. As a second step, we assess the direct, indirect, and demand-side welfare effects of energy and non-energy goods price increases by soft-linking results from the CGE with the estimation of a consumer demand system. The estimated demand system, based on the observed expenditures at the household level, allows us to consider the impact of policy-driven changes in relative prices on the whole consumption structure, accounting for differences in expenditure composition and substitution possibilities across the expenditure percentiles. To calculate the sources-side welfare impacts of the policy, we obtain from the CGE model the policy-induced factor price changes that we apply to the households' income distribution, accounting for the different income sources. Finally, we obtain the overall welfare effects of the policy, adding up both uses and sources-side impacts.

We contribute to the literature in several ways. First, by adopting a soft-linking approach between the CGE model and microsimulations with household-level data, we simulate the impact of a climate policy coherent with the EU targets and instruments on Italian consumers' expenditure patterns, providing a monetary quantification of the related welfare losses and distributional impacts. From a methodological perspective, our analysis for Italy brings novelties in assessing the uses-side distributional impact of a climate policy by considering direct and indirect effects and demand-side adjustments across different expenditure levels. Even though the issue of the potential regressivity of carbon pricing has already been investigated at country and cross-country scales, only a few contributions have explicitly considered all the potential uses-side effects on households' welfare.

Finally, we provide an estimate of the overall evaluation of the welfare effects of the climate policy by also simulating the welfare consequences of changes in the households' income distribution as a consequence of the policy-induced factor price changes. This simulation is also carried out by assuming that the policy revenues are invested in the Innovation Fund to support the development of clean energy technologies. This adds to the current debate on the potential negative impacts of climate policies by quantifying the potential distributional benefits arising from an approach based on the Energy Tax Reform theory (Ekins and Speck, 2011). To the best of our knowledge, this is the first contribution that simulates the sources-side impact of a climate policy for Italy.

Looking only at the uses-side effects, our results detect a mildly progressive distribution of the burden of the simulated climate policy scenario when all price changes and demand-side effects are considered. When we consider the impact of price changes on different goods categories, we find that isolating the effects related to food prices, the policy has a regressive impact on households' welfare. This highlights the relevance of considering climate policies' direct and indirect effects. When we also include the sources-side impacts, the progressivity of the policy is strengthened. Quite interestingly, in the scenario where we simulate reinvesting the revenues generated by carbon pricing mechanisms to finance innovation in clean energy technologies, we find that sources-side effects are positive for all quintiles. In the scenario without Innovation Fund investments, the burden is negative, except for the two lower quintiles.

[3] In setting out the enabling conditions needed to achieve the priority objectives of the Action Programme, Article 3 requires, among others, the phasing out of "environmentally harmful subsidies, in particular fossil fuel subsidies, at Union, national, regional and local level, without delay" and "setting a deadline for the phasing out of fossil fuel subsidies consistent with the ambition of limiting global warming to 1,5 °C (Decision (EU) 2022/591 of the European Parliament and of the Council of 6 April 2022 on a General Union Environment Action Programme to 2030; L 114/32).

[4] In 1999, a carbon tax on the consumption of energy products that mainly hit transport fuels was first introduced and then removed eleven months after entering into force, partly as a consequence of the distributional concerns in a period of surging world oil prices (Tiezzi, 2005).

The policy implication we derive is that through dynamic and model-based impact evaluation analyses, it is possible to assess the potential burden households might suffer from climate policies coherent with the EU targets. By soft-linking a CGE model with a demand system analysis, we have the advantage of considering the different demand responses of households at different income levels and, consequently, the different welfare impacts along the income distribution. This may help policy-makers elaborate on potential corrective measures to increase the public acceptability of ambitious climate targets.

The rest of the paper is structured as follows. In Section 2 we review the relevant literature to frame our contribution. In Section 3 we describe the main methodological tools and choices: the dynamic CGE model, the demand system specification, and the soft-linking method. In Section 4 and Section 5, we describe the dataset and discuss estimation results related to the expenditure side. In Section 6, we perform the simulation exercise on sources-side effects. Section 7 concludes with some policy implications.

2. Literature review

Three strands of literature are relevant to our analysis. The first includes contributions that analyze the distributional consequences of climate policies on the uses of income side. Several comprehensive reviews (Fullerton, 2009; Wang et al., 2016; Pizer and Sexton, 2019) show that the literature yields ambiguous results. Even though the relatively higher burden of energy goods in the budget of households with lower incomes suggests expecting a regressive impact of carbon pricing, some studies find proportional or even progressive outcomes. Pizer and Sexton (2019) conclude that the regressive effect of energy taxes depends on the type of product that is taxed: taxes on electricity are regressive, while gasoline taxes are progressive in some countries and over some income ranges. Similar conclusions are reached by Wang et al. (2016) for a set of developed countries. Other studies show that taxes may have different distributional effects depending on the country's economic development level (Tol and Verde, 2009). Ohlendorf et al. (2021) show that adding the indirect impact of carbon policies on the price of goods different from energy ones may lead to a different distributional picture, depending on the relative carbon intensity of the consumption basket of poorer and richer households. Hassett et al. (2009) find that the direct effects of a carbon tax in the US mainly contribute to the regressivity, while the indirect effects appear mildly progressive. In contrast, other studies find that the regressivity is increased when indirect effects are considered, as poorer households tend to spend a larger proportion of their income on energy-intensive goods (Jacobsen et al., 2003; da Silva Freitas et al., 2016).

A key methodological choice in the literature is the inclusion of demand-side adjustments or behavioral reactions to policies. The rationale for using carbon pricing is to stimulate consumers to substitute energy-intensive commodities. Disregarding demand-side adjustments may thus compromise the models' ability to capture the overall effect of climate policies. When demand adjustments are included, the distributional outcome of the simulation depends both on pre-tax expenditure patterns and on the relative difference in demand elasticity between high and low-income groups. West and Williams (2004) provide an important contribution in this respect. They evaluate the distributional impact of a gasoline tax increase using four incidence measures differing in their ability to capture the demand responsiveness to price changes. By estimating a consumer demand system on the US Consumer Expenditure Survey data (1996–1998), the authors show that the overall tax burden is overstated when estimations ignore the reduction in gas consumption in response to the increased tax. The regressivity of the impact is also overestimated, neglecting the lower gas demand elasticity of the top quintile compared to others. Schulte and Heindl (2017) show that the behavioral responses to energy price changes are weaker for low-income than richer households. In other studies, on the contrary (e.g., Labandeira et al. (2006) for Spain), poorer households appear to be more responsive to changes in energy prices.

Reaños and Lynch (2022) highlight the importance of disentangling the welfare impacts of carbon taxation between the loss of purchasing power and the substitution effects implied by changes in relative prices. The evidence they provide for Ireland reveals that the main channel of the regressive impact of the tax is the decrease in purchasing power, which disproportionately affects vulnerable households. However, they also find that the demands for heating fuels and private transportation are complementary in their data. As a result, taxes on fuels used for private transport can reduce the energy demand in the residential sector, increasing welfare losses. A similar decomposition is also carried out by Pashardes et al. (2014) for Cyprus.

Concerning Italy, the evidence about the relatively higher burden of carbon pricing for poorer households is not conclusive. Distante et al. (2016) find that removing energy subsidies would mostly affect the middle class. Faiella and Lavecchia (2021), considering only the direct effects of carbon taxation, find regressive effects. In a seminal contribution, Tiezzi (2005) exploits the temporary introduction of a carbon tax in Italy in 1999. Estimating a linear demand system based on the Italian household budget survey data from 1985 to 1996, the author shows that the price increases induced by the tax create a substantial aggregate welfare loss, increasing with the household income level. Distefano and D'Alessandro (2023) study the long-term impacts of a gradually increasing carbon tax in Italy, using numerical simulations based on a dynamic macrosimulation model. According to their results, if the carbon tax revenue is redistributed to low-income groups, and assuming that consumers and firms follow adaptive behaviors, a 'quadruple-dividend' can be achieved: emission reduction and better economic performance, coupled with a reduction in income inequality and sustainable public indebtedness.

The second relevant strand of literature includes contributions that estimate the effects of climate policies by combining macro and micro modeling. The efforts to link CGE models with microdata can be classified into three groups (Bourguignon et al., 2008): top-down, bottom-up, and fully integrated models. In this paper, we adopt the first approach. Top-down models, first, compute the general equilibrium effects of a policy intervention on commodity prices and primary factor returns; then, they use these price variations as the "linkage" variables in microsimulations (Hamilton and Cameron, 1994; Metcalf et al., 2008; Labandeira et al., 2009; Araar et al., 2011; Vandyck and Van Regemorter, 2014; Vandyck et al., 2021; Feindt et al., 2021).

The third strand of literature includes those contributions that explore the sources-side effects of carbon pricing. Metcalf (2021) underlines the need to consider the impact of a carbon tax on factor prices in determining its overall distributional consequences. On this side, a progressive effect of the tax may be expected if returns to capital decrease more than wages and/or if poorer households' incomes are disproportionately affected by the existence of indexed transfers that automatically adjust the cost of living when energy prices increase.

One of the first contributions identifying this progressive effect through indexed government transfers is Rausch et al. (2011). The authors investigate the distributional impact of different allowance allocation schemes in the US economy, finding that carbon pricing is proportional to modestly progressive, even excluding the return of carbon revenues. In the model, carbon pricing does not affect transfers, while wages and return to capital are affected. Fullerton et al. (2012) examine the impact of different assumptions on the degree of transfer indexing on the carbon tax incidence. When households' expenditures are considered a proxy of welfare, the authors find that the sources-side impacts offset the regressive uses-side impacts. Williams III et al. (2015) show that recycling revenue from a carbon policy as a lump sum rebate to households counteracts its regressive impact, sustaining incomes of the poorest quintiles. On the contrary, using revenue to reduce capital taxation exacerbates the regressivity. The most relevant contribution to our work in this literature is Goulder et al. (2019), which derives a

quantitative measure of the sources and uses-side impacts of a carbon tax. Specifically, the welfare impacts of the policy are measured using the equivalent variation, where the two (uses and sources-side) components are first calculated separately and then aggregated coherently to obtain the overall welfare change.[5] In their analysis, the uses-side impacts are always regressive under all revenue recycling options, while the sources-side effects are generally progressive. Summing both impacts, the overall impact of the carbon policy is either progressive or close to proportional depending on the type of revenue recycling.

3. Methodological approach

3.1. The CGE model

To assess the distributional effects of our policy scenario, we adopt a sequential top-down approach, where first, the CGE model quantifies the effects of the policy on commodity prices. Then, using a micro-econometric model, we estimate the households' demand parameters. Finally, we calculate the welfare effects of the price changes using the micro model's demand parameters and the macro model's relative price changes. This approach has the merit of being simple and flexible. Indeed, while the CGE model accounts for the relevant inter-sectoral effects of the policy scenario on the supply and demand of the different goods, the micro-model allows us to incorporate in our analysis the households' behavioral responses.[6]

Concerning the estimation of commodity price changes (and factor price changes in the second part of the analysis), we rely on the recursive dynamic CGE model developed by Antimiani et al. (2023). This model is based on GDynEP, using the energy version of the dynamic GDyn (GDynE) model by Golub (2013), merged with the GTAP-Power (Peters, 2016) which includes a detailed representation of the electricity sector. The database version used for region and sector representation is GTAP10. The complete description of the model and policy simulations is provided in Antimiani et al. (2023). Here, we simply recall the main aspects of the simulations relevant to our study. The business as usual (BAU) scenario, with full recovery from COVID-19 by 2025, is compared with a policy scenario based on a combination of the complete phase-out of fossil fuels (FF) subsidies and a carbon tax (CT).

The removal of fossil fuel subsidies is modeled as a phase-out of all exemptions and tax rebates with an exogenous shock applied to the price of fossil fuels on the commodity market. The phase-out of these subsidies increases the price faced by agents that use fossil fuels as inputs or final consumption goods. The carbon tax is instead modeled as a carbon price, introduced by assuming a common permit market where all agents participate and no free allowances are provided. Such a design corresponds to the full implementation of the EU ETS with complete auctioning for all sectors, where the equilibrium carbon price corresponds to the Pigouvian carbon taxation. The model endogenously determines the equilibrium carbon price coherent with the climate target, considering all emissions associated with the fossil fuel inputs used by all agents and the contribution provided by the subsidies phase-out. The climate target is exogenously set and equals the emissions reduction needed to be on track with the carbon neutrality path in 2050 and the intermediate 55% reduction w.r.t. 1990 level envisaged by the Fit for 55 Package. By 2030, in the BAU scenario, the EU is expected to emit around 2989 Mton of CO2-eq, while the policy case target would require 2213 Mton of CO2-eq (corresponding to a 26% reduction w.r.t. the BAU levels in 2030). The common EU carbon price resulting from the simulation to fulfill the 2030 target without any additional policy instrument (as the complete functioning of the Innovation Fund) is 65 US dollars per ton of CO_2-eq in real terms (very close to the average carbon price of the first six months of 2024 on the EU ETS market).

We link the CGE results into the microsimulation model by isolating the price variation of final commodities induced by the policy from the GDynEP simulations. Given the detailed representation of 36 sectors, domestic market price changes from GDynEP are aggregated into the ten sectors of the demand system as the average of sector-specific price changes weighted by the relative consumption value of households. Price variations from GDynEP incorporate interactions between economic sectors and additive effects due to the simultaneous implementation of the two policy instruments (CT and FF), considering the full network of global linkages, especially for trade flows. Accordingly, the averaged ten sectors' price changes from GDynEP can capture all market-based interactions occurring after the policy implementation.

Two limitations in soft-linking GDynEP results to the demand system estimation model should be accounted for when interpreting the results. First, there is a discrepancy in timing between the estimation of the demand system and the CGE model. GDynEP provides price variations with yearly intervals, but identifying parameters in the demand system necessitates a higher degree of price index variability across time. Accordingly, we use monthly price indices in the baseline demand estimation to capture short-term consumer reactions. Then, we apply the year-based price changes from the CGE to assess the impact of different (yearly-based) price effects on welfare and distribution at the household level.

Second, price variations in policy scenarios are calculated by considering the European Union (EU27) as a whole, given that the GDynEP model presents a single EU region with a common carbon price. There is, however, sufficient indirect evidence that the price changes simulated by the aggregate GTAP model at the UE level are sufficiently close to those that could be estimated for Italy only. Indeed, it can be shown that the price index patterns for the main good categories used in the analysis are similar based on the most common statistical tests. Also, the combined evidence of Berthold et al. (2023) and OECD (2024) illustrates that the aggregate price level response to carbon pricing in Italy is aligned with the average EU response, being the effect of carbon pricing on inflation dependent on the country's emission intensity, that is in Italy very close to the EU27 average. At the sectoral level, the evidence found in the literature for specific industries is not inconsistent with this picture (Neuhoff and Ritz (2019); Bai and Okullo (2023); Cludius et al. (2020)).[7]

[5] A more accurate description of the model proposed by Goulder et al. (2019) is provided in Section 6.1.

[6] Similarly to most previous studies, we perform an *ex-ante* evaluation of the policy adopting a unidirectional approach. This implies that feedback from the demand system estimation cannot return to the CGE model. This may appear to be a limitation of the soft-linking procedure as opposed to recursive models, where parameter values are updated (Callan et al., 2009; Mayer et al., 2021). Every approach, however, has its merits and shortcomings: the complexity of the recursive approach may require strong assumptions and simplifications, for instance, sacrificing the interrelations of the investigated country within the global economic network. Further, the choice of the model should also depend on the research aims. Recursive models are useful to evaluate the long-term impact of policy changes (Distefano and D'Alessandro, 2023), while, as argued by Bourguignon and Bussolo (2013), using a top-down model without feedback may be a correct methodological choice to evaluate the short-term impact of a macro policy (p.1389), as in our case. Finally, Fragkos et al. (2021) discuss the merits and limits of a hard link or a sequential-soft link approach and conclude in favor of the second. They justify their choice based on the empirical results by Rutherford et al. (2005) that find limited benefits from using the hard link modeling at the expense of a large increase in computational complexity.

[7] We also perform a robustness check and conduct a sensitivity analysis on the price changes of the commodities mostly relevant to our analysis. Specifically, we consider short-term differences between the Italian and EU27 series of prices and apply the average percentage variations to the price changes obtained by the GDynEP model to account for potential deviations of Italian prices to EU price changes induced by the policy. Our distributive results, available upon request from the authors, are fully confirmed.

3.2. The demand system estimation

The welfare effects of the price changes induced by the simulated policy are modeled by estimating a complete system of demand equations for ten composite good classes. The estimation of the demand system provides direct and cross-price elasticities at different income levels, enabling us to account for different demand responses of households at different levels of income distribution. This, in turn, allows us to capture the heterogeneous welfare impacts of the climate policy on households with different incomes.[8] To estimate the demand system, we adopt the Quadratic Almost Ideal Demand System (QUAIDS) developed by Banks et al. (1997), which is an extended version of the Almost Ideal Demand System (AIDS) by Deaton and Muellbauer (1980a) with a quadratic term in real expenditure. The additional term allows Engel curves for some goods to be non-linear in total expenditure. The choice of the QUAIDS model has been supported by a semi-parametric analysis of Engel curves in the spirit of Banks et al. (1997) and Reaños and Wölfing (2018), graphically showing the presence of higher-order terms for private transport, electricity, healthcare, leisure, and residual expenditure (see Appendix A.3).

The dependent variables of the system are the expenditure shares (w_i), jointly determined by the relative price indices ($\mathbf{p}$), the level of total expenditure (m), and a set of demographic and geographical controls acting as demand shifters[9]:

$$w_i = \alpha_i + \sum_{j=1}^{K} \gamma_{ij} \ln p_j + \beta_i \ln \left[\frac{m}{a(\mathbf{p})}\right] + \frac{\lambda_i}{b(\mathbf{p})} \left\{\ln \left[\frac{m}{a(\mathbf{p})}\right]\right\}^2 \quad (1)$$

$$\forall \quad i, j = 1 \ldots K$$

where $K = 10$ stands for the number of composite goods, indicated by the subscripts i and j, while $a(\mathbf{p})$ and $b(\mathbf{p})$ are the translog and Cobb–Douglas price aggregators, respectively.[10] The parameter γ captures cross-price effects,[11] the parameter β captures the linear relation between real expenditure and w_i and λ captures potential non-linearities in the relation between w_i and real expenditure.[12]

The model estimation imposes that the conditions of adding-up, homogeneity, and symmetry are satisfied to ensure the integrability of the model, i.e., its consistency with the assumption of rational consumer behavior. The system's parameters allow us to derive price and expenditure elasticities and the cost functions underpinning welfare measures in the distributional analysis. The cost function takes the form:

$$\ln m(V, \mathbf{p}) = \ln a(\mathbf{p}) + \frac{\ln V(\mathbf{p}, m) b(\mathbf{p})}{1 - \lambda(\mathbf{p}) \ln V(\mathbf{p}, m)} \quad (2)$$

and is obtained by inverting the indirect utility function of the QUAIDS (Appendix A.1). The function indicates the cost of attaining the level of utility V at a given price structure $\mathbf{p}$.

The expenditure elasticities (e_i) are calculated by deriving the demand functions with respect to $\ln m$, while the (compensated) price elasticities (e_{ij}^C) are obtained by deriving the demand functions with respect to $\ln p_j$.

When estimating demand systems, the presence of observations with zero expenditure in the dependent variable can lead to inconsistent parameter and elasticity estimates. In our dataset, for some classes of goods, the share of households reporting null expenditures is relevant (see the last column in Table 1 in Section 4). To account for this issue, we estimate a censored version of QUAIDS in a two-stage procedure following Shonkwiler and Yen (1999): first, the probability of having non-negative expenditures is estimated with a univariate probit for each composite good; second, the unconditional expectation of expenditure shares, modeled as in Eq. (1), are obtained using the cumulative and density distribution functions from the first stage.[13]

The estimation of demand parameters is needed to calculate the welfare effects of price changes. Following Deaton and Muellbauer (1980b), under the assumption of constant expenditure, the welfare change caused by a variation in relative price indices can be measured by the compensating variation (CV) (see Appendix A.2), which is the amount of money a consumer would have to be compensated for after a price change to maintain the same level of welfare as before. The CV can be obtained as a function of the True Cost of Living Index ($TCOL$), which is the ratio of the cost functions before and after the price change at a fixed level of utility:

$$TCOL = \frac{m(u^0, \mathbf{p}^1)}{m(u^0, \mathbf{p}^0)} \quad (3)$$

where $m(u, \mathbf{p})$ are the cost functions, while $\mathbf{p}^0$ and $\mathbf{p}^1$ indicate the vectors of price indices before and after the price change. In other terms, the $TCOL$ index compares the cost of achieving a given level of welfare before and after a price increase. The $TCOL$ can be calculated from the parameter estimation of the demand system. When prices change, agents react to the variation in the real value of their resources and to changes in the price structure that may modify the relative convenience of goods. The advantage of the $TCOL$ is that it considers substitution possibilities that may allow households to stay at the same level of utility by changing their consumption patterns. Specifically, with $TCOL$, two separate issues can be included in the analysis: (i) non-homothetic preferences and (ii) substitution effects.[14] Non-homothetic preferences make the index depend on a reference level of utility or expenditure (m^0), so price changes may affect households differently if they have different patterns of expenditures (Deaton and Muellbauer, 1980b).[15] Substitution effects that affect households' welfare through variations in the relative convenience of goods are captured by γ parameters of the demand function. From the $TCOL$, the CV is obtained as:

$$CV = m(u^0, \mathbf{p}^0)(TCOL - 1) = m(u^0, \mathbf{p}^1) - m(u^0, \mathbf{p}^0) \quad (4)$$

Being derived from the Hicksian demand curve and representing a money-metric measure of welfare, the CV is a precise measure of the change in welfare which follows a price change and, in particular, a valid measure when non-homothetic preferences are assumed (Deaton and Muellbauer, 1980b,a).

4. Data

For our simulations, we use seven cross-sections of the Italian Household Budget Survey (IHBS 2014–2020), which provides monthly expenditure data for a representative sample of the Italian population,

[8] This is the advantage of soft-linking the macro model with the demand system estimation. The CGE model accounts for all the general equilibrium effects of price variations. However, referring to a representative agent, the distributional impacts of price changes on households at different income levels cannot be estimated.

[9] Here demand and cost functions are reported without the demographic controls, see Appendix A.1 for the complete formulation.

[10] See Appendix A.1 for $a(\mathbf{p})$ and $b(\mathbf{p})$ definitions and detailed calculations throughout this section.

[11] The effect of changes in prices of other goods, indicated by p_j, on the share spent on good i (w_i).

[12] λ is the parameter introduced by Banks et al. (1997).

[13] When values of the dependent variable pile up at zero it is indeed not possible to use a continuous density to explain the conditional distribution of expenditure. The 2-stage procedure solves the problem by modeling the dependent variable as a Tobit Type 2 model, where a separate stochastic process estimates the censoring of each dependent variable.

[14] The first economic implication of non-homothetic preferences is that the budget composition can be set to depend on total expenditure, hence not all expenditure elasticities have to be unity. The second implication concerns the structure of the cost function: the cost of increasing utility is not necessarily proportional to the utility change.

[15] Specifically, the term $b(\mathbf{p})$ amplifies the effect of price changes on higher expenditure households.

sampled sequentially over quarters each year. The survey standardizes the collected data to a common temporal reference, the month so that all expenses can be summed up.[16] The decision-making unit is the household. Despite households remaining in the sample for three months, it is not possible to identify repeated monthly observations for the same household in the microdata, thus we treat them as independent. Following Banks et al. (1997), we trimmed observations beyond three standard deviations of the mean of expenditures. This leaves us with a final sample of $N = 116,195$ households (approximately 16,600 observations per year). Together with information on all expenditures in goods and services for household consumption, the survey also collects demographic characteristics, dwelling and vehicle ownership details, and other information connected to consumption habits.

We estimate the demand system on ten composite good classes: food, public transport,[17] private transport, gas,[18] other heating fuels,[19] electricity, clothing, healthcare, leisure, and residual.

We have grouped consumption categories to have detailed expenditures on energy commodities while retaining enough variety in other general expenditures. This is coherent with Reaños and Wölfing (2018), who recommend keeping a realistic picture of the households' consumption structure, arguing that clustering several categories into only one imposes strong assumptions on the preference structure with implausible implications on substitution and income effects. Modeling transport fuels, public transport, heating, and electricity separately allows us to shed light on the elasticities of these goods at different levels of income and on potential substitution patterns. The classes directly correspond with the European Classification of Individual Consumption according to Purpose (ECOICOP) while isolating energy goods. Following standard practice in the literature, durable goods were excluded as the model does not account for inter-temporal consumption decisions,[20] and the total current expenditure is net of housing costs.[21] The average shares of the classes are shown in Table 1, together with mean shares of the top (Q5) and bottom (Q1) quintiles and the proportion of households reporting null expenditures in each class ($w_i = 0$).[22]

The ECOICOP consumption aggregation allows us to directly link expenditure groups to consumer price indices following the same classification. We use the Consumer Price Index (NIC) issued by the Italian National Statistical Institute (ISTAT) at the monthly frequency and regional level (January 2014 = 100), building weighted composite price indexes for our classes of goods.[23] Following the previous literature (Banks et al., 1997; Tiezzi, 2005), we merge prices and expenditure data to retain the temporal variation of relative price indices and investigate how they impact consumption patterns. Trends in price indices for our categories are plotted in Fig. 1.

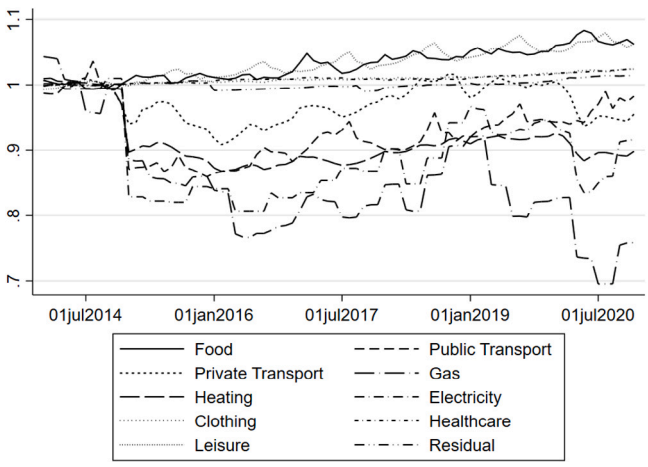

Fig. 1. Price indices trends (ISTAT NIC).
Note: Own elaboration on Istat data, 2014–2020.

Price indices show different trends in the period of interest. The bundle of energy goods – transport and domestic energy expenditures – report values consistently below the level of January 2014 throughout the period of interest. For the remaining good classes, moderately but steadily increasing patterns can be detected. The public transport price index is characterized by seasonal cycles with peaks in August.[24] For private transport, it is possible to detect a deflationary trend in 2014–2016, followed by a recovery and a stabilization at reference levels (January 2014) in 2019 and a decrease in the final year. Gas and electricity indices follow the same trend over time. The other heating fuels index is a weighted average of liquid and solid fuels price indices and is less subject to gas price fluctuations. From 2019, we observe divergences in trends of gas and electricity prices, with heating persistently below the January 2014 level (in Appendix B energy goods price trends are plotted separately).[25] The residual price index slightly increases over time (1%). The discontinuity in January 2016 is driven by education prices, plummeting in 2016 due to the university fees reform (Law Decree No. 232/2016).[26]

Fig. 2 shows the average expenditure shares for different good categories of households grouped according to their total expenditure. Expenditures on food and energy represent a larger share of the budget of poorer households. By contrast, the remaining expenditure shares increase with total expenditure levels.

Fig. 3 focuses specifically on households' expenditure for energy goods. The shares decline consistently across the distribution. The average household in the lowest quintile devotes about 15.5% of its budget to purchases of domestic energy. In comparison, the average household in the highest quintile spends only 5% on the same commodities. This figure seems to confirm the conventional wisdom that

[16] The investigation detects expenses with very different reference periods (e.g., food expenditure is collected over periods of 14 days, healthcare over the past 3 months, and dwelling expenditure over the past 12 months), so standardization is needed to sum them up.

[17] Public transport includes expenditure for passenger transport by train, metro and tram, bus and coach, taxi, sea, and inland waterway, and combined passenger transport. It also includes passenger transport for students to and from school. Transport by airplane was excluded because of the high price seasonality of flight tickets.

[18] The survey does not allow to separate expenditure on gas used for heating spaces from that for other purposes (heating water, cooking). The large majority of households (75%) use gas as space heating fuel, 11% use wood, pellets, and alike, 5% bottled gas, 3% gasoil, kerosene, and the remaining electric energy, solar panels, or other fuels.

[19] Other heating fuels include butane and other liquid gases, kerosene diesel and other liquid fuels, coal and wood

[20] Expenditure on durable constitutes on average 3.7% of the total expenditure.

[21] Housing expenditure in the survey is recorded as imputed rentals for owner-occupiers and actual rentals. Since imputed rents are notional values of the dwelling of residence, we do not include them among household expenditures. Accordingly, we also exclude actual rentals. Including housing expenditure only for households paying rent would unwarrantedly place them on top of the total expenditure distribution. Housing expenditure corresponds to 30% of the total expenditure.

[22] Methodological notes provided by ISTAT clarify that zero expenditure on food in a given month can be explained by home production, wholesale purchases made in previous months, or gifts. Instead, public programs funding electricity bills for low-income households explain zero values for expenditure on electricity bills.

[23] The price data used in this paper are not publicly available but come from an *ad hoc* elaboration from ISTAT, to have the highest spatio-temporal variability (month-region cells) at COICOP 3-digits level.

[24] The index does not include flight prices; in this case, the seasonality would be even stronger.

[25] The drop in energy prices in January 2015 is documented by ISTAT here: https://www.istat.it/it/archivio/150991.

[26] https://www.istat.it/it/archivio/213708.

Table 1
Average Expenditure Shares.

	Mean	SD	Q1	Q5	$w_i = 0$
Food	0.315	0.14	0.374	0.256	0.70%
Public transport	0.006	0.02	0.005	0.007	77.9%
Private transport	0.091	0.09	0.047	0.109	27.4%
Gas	0.039	0.05	0.062	0.023	22.3%
Other heating fuels	0.011	0.03	0.019	0.005	65.2%
Electricity	0.043	0.04	0.078	0.022	2.00%
Clothing	0.053	0.07	0.033	0.070	39.5%
Healthcare	0.060	0.08	0.065	0.057	24.4%
Leisure	0.130	0.11	0.068	0.184	7.50%
Residual	0.252	0.12	0.246	0.266	0.10%

Note: Own elaboration on the Italian Household Budget Survey (Istat) 2014–2020, N=116,195.

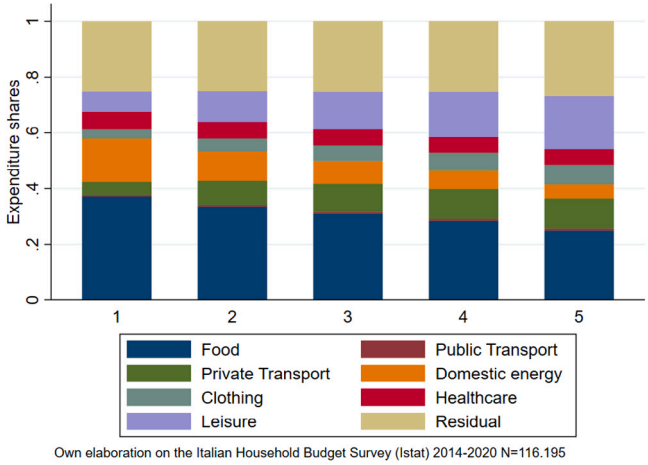

Fig. 2. Expenditure shares by quintile.
Note: Own elaboration on the Italian Household Budget Survey (Istat) 2014–2020, N=116,195.

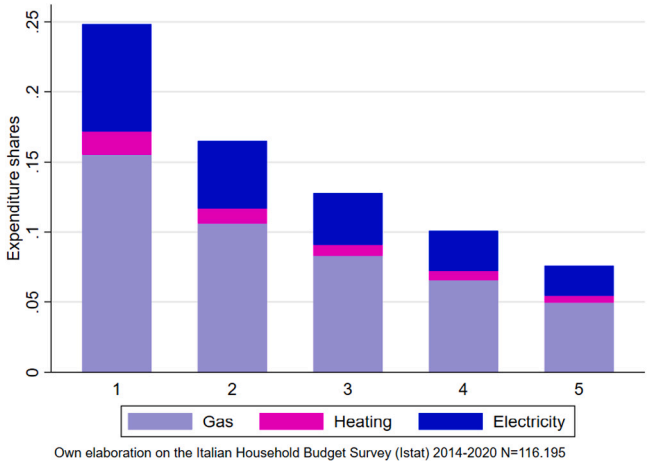

Fig. 3. Domestic energy expenditure shares by quintile.
Note: Own elaboration on the Italian Household Budget Survey (Istat) 2014–2020, N=116,195.

policies that affect the price of energy goods are regressive. Given the differences in the average shares of total expenditures on energy goods consumption across groups, poor households will bear more tax burden than rich households. Electricity and gas expenditures especially drive the regressivity: households in the poorest quintile spend almost 8% and 6% of total expenditure on electricity and natural gas, respectively, more than triple the corresponding spending for the wealthiest quintile.

In contrast, the expenditure share of private transport increases with the total expenditure, suggesting a potential countervailing effect of

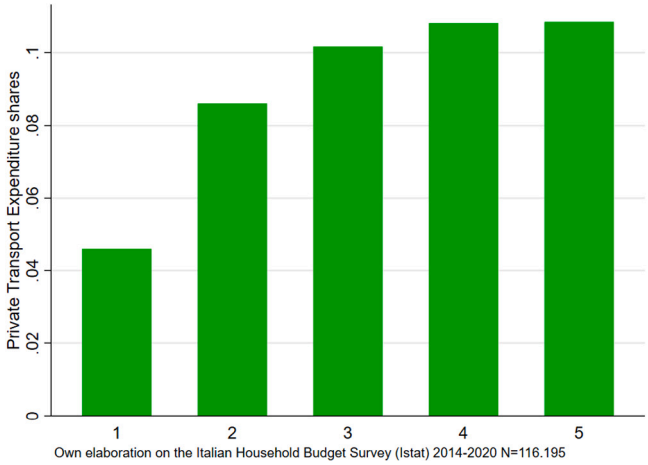

Fig. 4. Private transport expenditure shares by quintile.
Note: Own elaboration on the Italian Household Budget Survey (Istat) 2014–2020, N=116,195.

the regressivity of carbon pricing (see Fig. 4). Households in the first quintile spend less than 5% of their annual expenditure on private transport, while those from the third quintile to the highest spend more than 10%. The consumption pattern for private transport which characterizes Italian households is peculiar compared to other countries, where instead, the average household's motor fuels expenditures as a percentage of total spending are mildly decreasing with income, like in the US, or where the greatest expenditure share are incurred by households in the middle of the distribution, like in the UK (Pizer and Sexton, 2019). These differences suggest that the distributional impact of carbon price also depends on country habits and cultural factors (e.g., vehicle ownership rates) and the availability of public transport infrastructures.

5. Demand system estimation results

5.1. Elasticities

Estimating the demand system requires finding a well-behaved specification of demand functions, integrable into a consistent preference ordering. This condition is satisfied when the Slutsky substitution matrix is negative and semi-definite. To find a proper model specification, we progressively add covariates to the specification in Eq. (1), starting from a more parsimonious form and then including household size, the area of residence, and the age of the household head as controls (Table 2).[27] In the following analysis we use Model 3.

[27] Estimation is conducted by iterative feasible generalized nonlinear least-squares using the Stata command *quaidsce* that extends the *quaids* command to

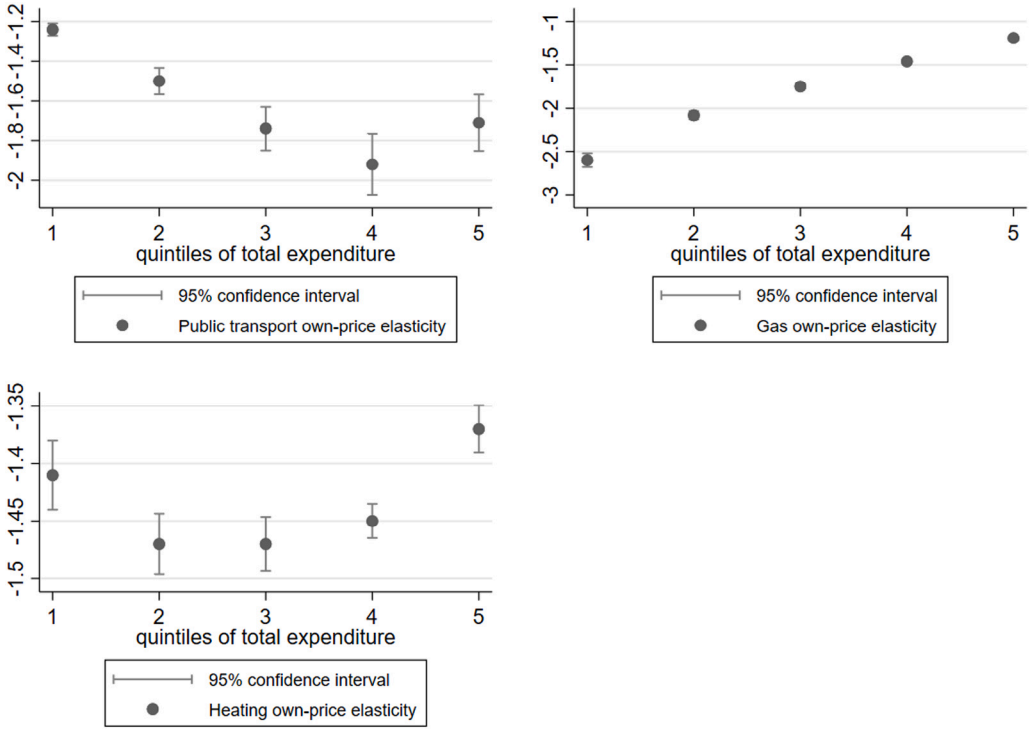

Fig. 5. Price elasticities by quintile.

Table 2
Model specification.

	Model 0	Model 1	Model 2	Model 3
Household size	No	Yes	Yes	Yes
Area of residence	No	No	Yes	Yes
Age of household head	No	No	No	Yes
Log-likelihood	2517370.8	2509325.9	2505247.7	2464677.8

Table 3
Elasticities.

	e_i^C	SE	e_i	SE
Food	−0.10	(0.08)	0.72	(0.003)
Public transport	−1.72	(0.06)	−0.17	(0.037)
Private transport	−0.47	(0.03)	1.58	(0.003)
Gas	−1.82	(0.02)	1.08	(0.006)
Other heating fuels	−1.49	(0.01)	0.62	(0.011)
Electricity	−1.25	(0.10)	0.26	(0.010)
Clothing	−1.57	(0.03)	1.20	(0.007)
Healthcare	−0.78	(0.02)	1.20	(0.005)
Leisure	−0.29	(0.02)	1.43	(0.003)
Residual	−0.27	(0.13)	0.97	(0.004)

Note: e_i^C is the estimated own-price elasticity and e_i is the estimated expenditure elasticity.

Table 3 reports compensated own-price elasticities and expenditure elasticities for the headline specification satisfying the theoretical restrictions of adding-up, homogeneity, symmetry, and negativity.[28] Table 3 shows that the elasticity matrix is negative semi-definite, as required. Gas, public transport, and clothing have more elastic demand to price changes, whereas the demand for food is the most rigid (e_i^C = −0.10).

Fig. 5, which reports only statistically significant differences in elasticities of energy goods across the expenditure distribution, shows that the elasticity for gas expenditure has an increasing pattern across quintiles (i.e. in absolute terms richer households have a more rigid demand), while public transport and heating price elasticities have a U-shaped form. These patterns can be explained by referring also to cross-price elasticities: the cross-price elasticity between gas and other heating fuels is statistically significantly higher in the bottom quintile than in the top quintile because of the relatively higher reliance on alternative heating fuels by poorer households.[29] This result is also coherent with results provided by Reaños and Wölfing (2018), according to which more affluent households in Germany typically react less to energy price changes than their poorer counterparts. Concerning transport modes, instead, as in Tiezzi (2005), we find that private and public transport are net substitutes (e_{ij}^C = 0.05). The cross-price elasticity increases across quintiles, being equal to 0.03 for the bottom and 0.29 for the top quintile, respectively, suggesting that wealthier households tend to substitute more the use of private cars with public transport modes when the price changes (even though the difference across quintiles is not statistically significant). A possible explanation for this finding is that wealthier households are concentrated in urban areas with more public transport availability (see Table 3).

Regarding the expenditure elasticities (Table 3), as in Schulte and Heindl (2017), we also find that all goods are necessities or luxuries. Only public transport is an inferior good. The expenditure shares devoted to private transport, gas, clothing, healthcare, and leisure increase more than proportionally with income. Food, heating, and electricity are instead necessities. In Fig. 6, we plot expenditure elasticities for energy goods by total expenditure quintiles. Public transport is an inferior good for lower quintiles and becomes a luxury for the top quintile. On the contrary, private transport is a luxury good along the

censored demand systems. The variance–covariance matrix is the asymptotic theory consistent *gnr*, using the variance estimator for nonlinear models fit derived with the Gauss–Newton regression.

[28] As reported in Appendix C, all system parameters are significant. We report the complete matrices of compensated and uncompensated elasticities in Appendix C.

[29] Alternative heating fuels, like kerosene and wood, are more easily available in rural areas, especially in the South of Italy, where poorer households are more concentrated.

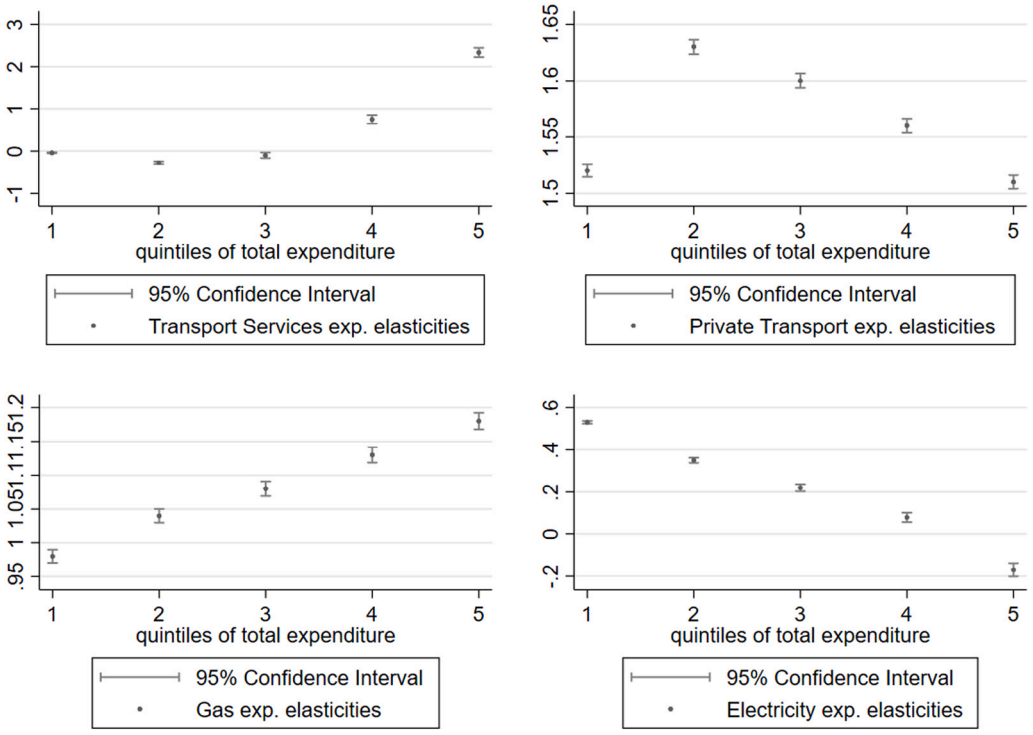

Fig. 6. Expenditure elasticities by quintile.

whole distribution: its elasticity increases from the first to the second quintile and then linearly decreases, reaching the minimum of 1.5 for the top quintile.

Gas is a necessity, in line with Schulte and Heindl (2017): income increases in the distribution's left tail increase less the demand. The elasticities for electricity, shown in the bottom-right panel of Fig. 6, follow an opposite pattern, and electricity becomes an inferior good for the top quintile. A possible explanation for this pattern is that electricity expenditure in absolute value is stable across quintiles.

5.2. Welfare analysis

The estimation results presented in the previous section are used to compute the welfare effects of the policy scenario described in Section 3. Commodity price variations between 2020 and 2030 induced by the simulated policy are compared with the baseline scenario (BAU), accounting only for climate policies implemented by the EU before January 2020. Price variations for our ten good classes are shown in Table 4.[30] After-tax price indices vectors ($\mathbf{p}^s$) are then obtained by adding these variations to ISTAT price indices (NIC), simulating the application of the climate policy between 2020 and 2030 in the data period 2014–2020 (see Table 4).[31]

We denote the vectors of price indices under the policy scenario with $\mathbf{p}^s$ and the baseline price indices vector with $\mathbf{p}^0$.[32] As explained in Section 3, the welfare change due to price variations can be measured by the CV. Accordingly, the welfare impact of the simulated policy for each household h (denoted by B_h) is given by the (money-metric) difference between the compensating variations before and after the price change[33]:

$$B_h = CV_h(\mathbf{p}^0) - CV_h(\mathbf{p}^s) \tag{5}$$

Table 5 shows the welfare losses associated with the simulated scenario by quintile of total expenditure. The losses are calculated using both weighted averages of individual compensating variations $CV_h(\mathbf{p}^s)$, and the ratio of B_h (Eq. (5)) over total household expenditures (Y_h). As

Table 4
Percentage points price changes w.r.t. BAU.

	Price change
Food	0.005
Public transport	5.13
Private transport	25.50
Gas	31.33
Heating	146.20
Electricity	8.58
Clothing	−0.54
Healthcare	−0.29
Leisure	−0.65
Residual	−0.60

Note: For each category, the price changes obtained from the GDynEP model are reported as a result of the simulated policy, expressed as percentage point variations with respect to the BAU scenario.

[30] The GDynEP-QUAIDS mapping is shown in Appendix D.1.

[31] This is commonly done to simulate *ex-ante* the impact of policy changes. The time proximity of the simulated scenarios to the last waves of available data (2014–2020) makes this assumption not too restrictive.

[32] See Appendix D.2 for details of the construction of baseline and policy price vectors.

[33] Computing the compensating variation requires evaluating the cost function at initial utility levels ($m(u^0, p^0)$); thus we can use the observed level of expenditure (m^0) that corresponds to the vector of price indices registered in the same year (p^0). As we explain in the following, the compensating variation is the most appropriate instrument for this part of the analysis. In the sources-side exercise, following the Goulder et al. (2019) framework, and to account for the income effect, we use instead the equivalent variation, holding the final level of expenditure fixed. The two values of the equivalent variation and compensating variation are similar in magnitude but not identical, as expected (Deaton and Muellbauer, 1980a).

Table 5
Welfare losses from the climate policy (euro\month).

Quintiles	$-CV(\mathbf{p}^s)$	SE	B_h/Y_h	SE
1	−14.72	(0.84)	−4.02%	(0.01)
2	−22.48	(1.52)	−4.30%	(0.01)
3	−32.05	(2.16)	−4.87%	(0.02)
4	−46.62	(2.97)	−5.62%	(0.02)
5	−47.82	(4.38)	−6.87%	(0.02)
K	0.099	(0.00)		

Note: For each quintile, the weighted average of individual compensating variations $CV_h(\mathbf{p}^s)$ is reported, together with the ratio of the difference between the compensating variations before and after the price change (B_h) over total household expenditures (Y_h). The bottom line reports the Kakwani index (K).

previously argued, the CV provides a cardinal index of welfare losses, corresponding to the monetary value of the average monthly welfare loss experienced by households in each quintile. The ratio B_h/Y_h can be interpreted as an incidence measure that measures the burden or welfare impact of the policy change per unit of the household's income/total expenditure, and it is commonly adopted to evaluate the distributional outcome of tax policies.

According to both welfare measures, households experience a decrease in welfare, with the absolute value of the loss increasing with total household expenditure.[34] The burden of the simulated policy is progressively distributed, with higher relative welfare changes for the top quintiles.[35] The bottom line of Table 5 provide the value of Kakwani index, one of the most widely used global measures of progressivity, which confirms the progressivity of the policy on the uses-side.[36]

To show the relevance of including demand-side adjustments in analyzing the effects of price changes related to climate policies on households' welfare, we compare the welfare losses calculated considering behavioral reactions with an alternative welfare measure, which does not account for them. In this alternative measure, based on the Laspeyres price index as a proxy of the true cost of living index, the household expenditure on each good has been increased proportionally to price increases. In other words, the welfare loss in this case corresponds to the additional expenditure incurred by households due to the price increases, assuming that the household demand does not change in reaction. Fig. 7 compares the welfare losses due to the simulated policy, calculated by the measure based on the CV and the measure based on the Laspeyres index (labeled as *static* as it does not account for behavioral reactions). As can be seen from Fig. 7, the static measure of welfare reports comparable welfare losses in magnitude (maximum

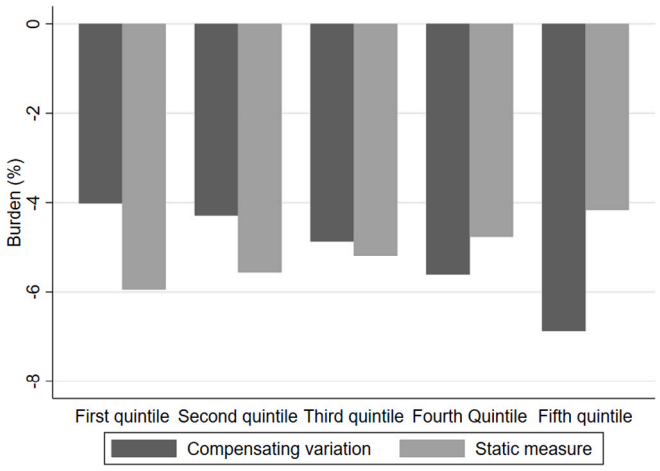

Fig. 7. Comparison of welfare measures.

and minimum values for the static measure and the compensating variation are 3.07% − 2.06% vs. 3.73% − −2.11%, respectively), but opposite results in distributional terms. While the welfare loss based on the CV is always increasing, moving from the first to the fifth quintile, identifying a progressive effect of the policy change, the welfare loss in terms of the static measure decreases across quintiles, outlining a regressive effect instead. This comparison highlights the merits of adopting a welfare measure based on the consumer theory, providing distributional consequences that contrast with the ex-ante presumption of the regressivity of energy taxes usually assumed in the tax evaluation literature.

Turning to the welfare results based on the consumer's demand system estimation, to assess whether specific price changes drive the progressive result, we decompose the welfare effect directly due to the change in the price of energy goods and the effect related to other indirect price effects. We calculate the welfare impact of price changes induced by the policy scenario for each product category at a time.

Kakwani indices for price changes of single commodities are reported in Table 6. For almost all good categories, the impact of the policy is progressive, even though the value of the index is very low in most cases, except for electricity. On the contrary, for food and, to a lesser degree, the residual category, the price increase leads to a regressive effect: in the case of food, the value of the index is even relatively high.

Fig. 8 graphically shows the different distributional effects of price increases due to the policy. For clarity, we have aggregated price changes in macro-categories of goods. Each curve describes the difference between the Lorenz curve of total expenditure at each percentile $[L_x(p)]$ and the concentration curve of the tax burden $[C_t(p)]$.[37] This difference is reported in Fig. 8 for different total expenditure percentiles and illustrates the (local) progressivity/regressivity of a policy change. The horizontal line at zero in the figure represents a proportional tax $[L_x(p) = C_t(p) \ \forall \ p]$ and is reported as a benchmark. Fig. 8 shows that the distributional profile of the price increase for food is always regressive.[38] at all percentiles, lying below the horizontal line.[39] The price increases for transport services (private and public) instead have

[34] Robustness-checks using total equivalent expenditure to rank households yields the same results in distributional terms.

[35] The progressive result on the uses-side, even though not common in the literature, is not particularly surprising. As highlighted by the review provided by Ohlendorf et al. (2021), considering indirect effects and demand-side adjustments in the distributional analysis increases the likelihood of finding proportional or progressive effects of carbon pricing. Especially in studies assuming non-homothetic preferences, progressive impacts are common, as price increases are allowed to have different effects for households at different levels of the expenditure distribution (e.g. Tiezzi (2005), Labandeira et al. (2009)).

[36] The Kakwani index, $K \in [-1, 1]$, compares the tax burden distribution with the income distribution. In the case of a proportional tax, for instance, the before-tax income curve and the tax curve overlap because the cumulative proportion of the tax paid is equal to the cumulative proportion of the perceived income. If the tax is progressive, the cumulative proportion of the tax paid by lower-income earners is less than the cumulative proportion of their income. The index is calculated as the difference between the tax concentration coefficient (the Gini index for the tax curve) and the Gini index for the before-tax income. When taxes have a higher (lower) concentration than income, the Kakwani index is positive (negative), and the tax shows a globally progressive (regressive) distributional profile.

[37] The concentration curve shows the cumulative proportion of taxes paid by each percentile of earners, ordered by their expenditure level. If the Lorenz curve (concentration curve) dominates the concentration curve (Lorenz curve), the tax is progressive (regressive).

[38] The regressive impact of the increase in food prices is driven by the higher expenditure share on food by low-income households relative to richer households. This result is not due to the aggregation of the meat and non-meat components of the food category. Looking at the expenditure share on

Table 6
Kakwani Indices for single good price changes.

Food	−0.27
Public transport	0.26
Private transport	0.12
Gas	0.07
Heating	0.12
Electricity	0.32
Clothing	0.08
Healthcare	0.03
Leisure	0.09
Residual	−0.02

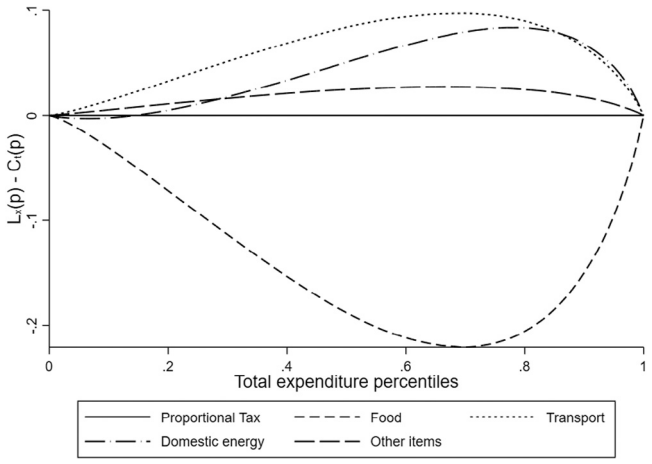

Fig. 8. Progressive effects of price changes across the expenditure distribution.
Note: Each curve describes the difference between the Lorenz curve of total expenditure at each percentile $[L_x(p)]$ and the concentration curve of the tax burden $[C_t(p)]$ for different total expenditure percentiles.

a progressive effect at all expenditure levels. Domestic energy (i.e., gas, heating, and electricity) price increases show a moderate profile of regressivity for the bottom percentiles and a progressive effect at higher expenditure levels. For the top expenditure classes, the domestic energy curve dominates the transport curve, suggesting a more progressive impact of this good category. This disaggregated analysis suggests that an indirect effect of the climate policy, namely the increase in food price, raises more concerns in distributional terms compared to the direct price effects of the policy, represented by price increases in domestic energy and transport.

6. Sources-side impacts of the climate policy

6.1. Framework and data

In this Section, we estimate the welfare impact of the simulated policy scenario by looking at the effects driven by changes in factor prices. To perform this analysis, we adopt the conceptual framework provided by Goulder et al. (2019). They suggest a quantitative measure of the overall welfare effects of a climate policy, disentangling the effects on individual utility due to its impact on returns to production factors and the prices of the purchased goods. The welfare impacts are measured using the equivalent variation (EV).[40]

In terms of the EV, the total welfare change, including both uses and sources-side effects, is the difference between the expenditure function at the final level of utility under the climate policy scenario (u^1) and the initial level of utility (u^0), without policy change, both calculated at the reference case price level:

$$EV^T = m(u^1, p^0) - m(u^0, p^0) \tag{6}$$

with u^0 and u^1, the indirect utilities, defined as $u^0 = V(y^0, p^0)$ and $u^1 = V(y^1, p^1)$.

In the demand system literature (Deaton and Muellbauer, 1980a; Banks et al., 1997), the equivalent variation is expressed as:

$$EV^{use} = m(u^1, p^1) - m(u^1, p^0) \tag{7}$$

i.e., the additional expenditure needed to achieve the same utility level (u_1) under different price regimes. After a price increase ($p_1 > p_0$), assuming that total expenditure does not change, households experience a decrease in welfare signaled by a positive EV^{use}. Isolating $m(u^1, p^0)$ from Eq. (7) and substituting it into Eq. (6), an expression for the total welfare change as the difference between the uses and the sources-side effects is derived[41]:

$$EV^T = EV^{source} - EV^{use} = m(u^1, p^1) - m(u^0, p^0) + m(u^1, p^0) - m(u^1, p^1) \tag{8}$$

where EV^{source} can be computed as the difference in total expenditure before and after the policy implementation. As in Goulder et al. (2019), we assume that the choice that maximizes households' consumption when only income varies is $C^{source} = \frac{y^1}{p^0}$, implying that $m(u^{source}, p^0) = y^1 = m(u^1, p^1)$. EV^{use} captures instead the change in welfare due to changes in relative prices and can be computed from demand system parameters as a function of the True Cost of Living Index (TCOL):

$$EV^{use} = m(u^1, \mathbf{p}^0)(TCOL - 1) \tag{9}$$

Assuming $p^0 = 1$ for all goods:

$$\ln TCOL = \ln a(\mathbf{p}^1) + \frac{\ln V^1 b(\mathbf{p}^1)}{1 - \lambda(\mathbf{p}^1) \ln V^1} - \ln m^1 \tag{10}$$

To link the microsimulation with GDynEP model results, we consider price variations under the policy scenario for three specific factors of production (endowments): unskilled labor, skilled labor, and capital. Price changes are displayed in Table 7. All factor prices decrease (unskilled labor relatively more) when fossil fuel subsidies are removed and the carbon pricing system is introduced to reach the 2030 mitigation target. In the CGE framework, the impact on factor prices is mainly driven by a reduction in the demand for inputs for domestic production, as energy-intensive processes are severely reduced and import flows replace final goods. Such a reduction in the demand for endowments explains the negative signs of price variation.

Given the potential relevance of technological change in increasing resource (inputs) efficiency and consequently modifying the impact on factor prices, the policy case is enriched by an additional instrument, working as the Innovation Fund (IF) included in the EU climate package. Specifically, we assume that revenues collected from the

meat, we still find a decreasing pattern across the income deciles (details are available from the authors upon request). Our result is coherent with other papers in the literature demonstrating the regressivity of carbon-equivalent food taxes (Kehlbacher et al., 2016; García-Muros et al., 2017; Klenert et al., 2023).

[39] Regressivity means that households in these percentiles receive a relatively smaller share of gross income/expenditure than they "pay" due to the price increase. By construction, the curves end at 0, as the two cumulative indices are both equal to 1 in the last percentile.

[40] The EV takes the final income level obtained after the policy-induced price changes as a reference to compute welfare variations. Although the EV requires more assumptions on the data (to obtain the final level of income), it is more appropriate for the sources-side exercise compared to the CV. The CV, which takes the initial income level as the reference, disregards changes in the income level caused by the policy and considers only changes in relative prices, as explained in Section 5.2.

[41] The expression is the same as in Goulder et al. (2019) where however we subtract the effects on the uses-side to keep the definition of the EV similar to Banks et al. (1997).

Table 7
Factor price changes from GDynEP (percentage points).

	Unskilled labor	Skilled labor	Capital
FF+CT	−1.91	−1.60	−1.62
FF+CT+IF	2.29	2.31	2.03

Note: Factor price changes from GDynEP are reported, expressed in percentage points. The first line refers to a scenario in which the effects of the phasing out of Fossil Fuel subsidies (FF) and the introduction of a Carbon Tax (CT) are simulated, while the second line considers also the effects of the Innovation Fund (IF).

phase-out of fossil fuel subsidies and the introduction of the carbon tax are fully reinvested in clean energy technologies. This reverses the sign of all factor price variations, as shown in Table 7. Investments in clean energy technologies are modeled in GDynEP as introducing energy efficiency in production and consumption processes and as an output technical change in producing energy from renewable sources. Thanks to the resource efficiency gain and the relative reduction in the cost of producing renewable energy, the demand for endowments in production processes is fostered, resulting in a positive (rather than a negative) price change.

In this latter case, where all pillars of the climate policy are in force (FF+CT+IF), the relative economic impact of achieving the emissions target is substantially reduced. The final carbon price endogenously computed by 2030 decreases from 65 to 29 US dollars per ton of CO2-eq, reducing the impact on price change for consumers. Indeed, the average price change w.r.t. BAU case without technological change is around 9.7%, while when the IF is implemented, the average price increase is only 0.74%.

To carry out the exercise that simulates the sources-side impacts, we resort to the Survey on Household Income and Wealth (SHIW) provided by the Bank of Italy, containing information on both consumption and incomes of Italian households, with details on income sources.[42]

The sample used in the most recent survey includes about 7000 households (16,000 individuals) distributed over about 300 Italian municipalities. In SHIW, household income is defined as the sum of income from employment, self-employment, capital income, and transfer income of all household members. The average annual total household income amounts to 48,160.70 euros (37,428.64 euros excluding imputed rents).

As shown in Fig. 9, income shares from different sources vary across deciles. Concerning labor income, we follow the GDynEP classification and distinguish skilled and unskilled labor.[43] The share of skilled labor income steeply rises as income rises, ranging from 5.76% in the 1st decile to 42.82% in the top decile, whereas income from unskilled labor is bell-shaped. Transfer income represents around 40% of income in the bottom four deciles (where pension incomes dominate) and steadily declines in the following deciles.

Capital income comprises income from rents (either imputed or not) and income or liabilities from financial activities. Imputed rents, i.e., the rental price an individual would pay for a housing unit equivalent to their own, represent, on average, 24.23% of total income, while received rents are only 0.9% on average; net income from financial activities (−0.12% on average) is the result of income from assets minus income from liabilities. The composition of the capital income

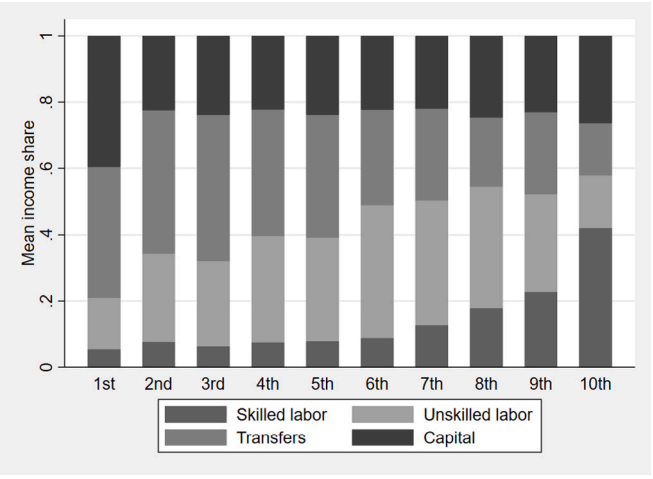

Fig. 9. Shares of income sources by income decile.
Note: Own elaboration on data from the Survey on Household Income and Wealth (SHIW), Bank of Italy.

component in Italy, hence, is peculiar because of the high weight represented by income from imputed rents. In contrast, income from assets represents only a negligible proportion of total capital income (0.8% on average). This peculiarity explains why capital income represents a declining share of total income, going from 41.56% in the bottom decile to 26.31% in the top decile.[44]

6.2. Simulation and results

To empirically simulate sources-side effects, we apply the factor price variations from the GDynEP model (Table 7) to the corresponding income typologies from the SHIW. Coherently with the literature (Goulder et al., 2019; Fullerton et al., 2012; Rausch et al., 2011), we adjust transfer incomes to inflation according to current rules in Italy. We then derive after-policy incomes for each household (y^1) defined as:

$$y^1 = (y^0_{SK} * GDynEP_{SK}) + (y^0_{UNSK} * GDynEP_{UNSK}) + (y^0_{CAP} * GDynEP_{CAP}) + (y^0_{TR} * GDynEP_{inf}) \quad (11)$$

The new income is then converted into a new expenditure (m^1).[45] From this conversion, we retrieve the average percentage variations in total expenditure by decile of total expenditure, corresponding to the sources-side effect (EV^{source}), as shown in Eq. (8). To obtain the second term (EV^{use}) of the Eq. (8), we apply the EV^{source} percentage variation by decile to total expenditures in the IHBS dataset (m^0), obtaining m^1 for each household. Then, we can compute the equivalent variation as in Eq. (9), using m^1 combined with the demand system parameters to evaluate the TCOL in Eq. (10).

Hence, in the following distributional analysis, we disentangle the three effects of the climate policy: the effect on the sources-side, depending only on changes in returns to factors of production; the effect on the uses-side, depending only on changes in final commodity prices; the total welfare effect, given by the sum of the previous two effects.

The welfare effects of the main policy scenario (FF+CT) are shown in Table 8. Sources-side welfare effects are positive in the first quintile

[42] The latest available wave refers to 2020. See: https://www.bancaditalia.it/pubblicazioni/indagine-famiglie/index.html.

[43] Skilled labor in GDynEP includes Technicians and Associated professionals, Officials and Managers, that we matched in SHIW with Officials and Managers, Entrepreneur and Self-employed, and Other self-employed. Unskilled labor in GDynEP includes Clerks, Service and Shop workers, Agricultural and Unskilled, matched in SHIW with Blue Collar workers and Clerks. Income from skilled and unskilled labor includes both income from employment and self-employment.

[44] It is lower in the ninth decile (23.33%) and then it rises again because, in the top decile, the shares of income from (not imputed) rents and financial assets are higher.

[45] To do the conversion, we apply the household-level marginal propensity to consume for positive income variations. In cases where income decreases, we assume consumption decreases by the same amount.

Table 8
Source and use-side welfare effects (FF+CT, EV in euro\month).

	EV source	Burden (%)	-EV Use	Burden (%)	Total	Burden (%)
First quintile	7.505 (0.06)	1.705 (0.02)	−46.330 (0.93)	−8.934 (0.17)	−38.825 (0.93)	−7.230 (0.17)
Second quintile	0.541 (0.07)	0.101 (0.01)	−81.814 (1.58)	−8.650 (0.16)	−81.273 (1.59)	−8.549 (0.16)
Third quintile	−7.943 (0.03)	−0.579 (0.00)	−123.241 (2.19)	−9.098 (0.16)	−131.185 (2.19)	−9.677 (0.16)
Fourth Quintile	−22.710 (0.14)	−1.176 (0.01)	−178.973 (2.94)	−9.471 (0.15)	−201.684 (2.96)	−10.647 (0.15)
Fifth quintile	−57.159 (0.25)	−1.962 (0.00)	−281.452 (4.26)	−9.743 (0.14)	−338.612 (4.33)	−11.705 (0.14)
K	0.492 (0.006)		0.022 (0.004)		0.069 (0.004)	

Note: For each quintile the equivalent variation for the sources-side impacts ($EV\ Source$), for the uses-side impacts ($EV\ Use$), and the total welfare impacts ($Total$) of the simulated policy are reported, together with the respective burden. The climate policy includes the removal of Fossil Fuel subsidies and the introduction of the Carbon Tax ($FF + CT$)). The bottom line reports the Kakwani index (K).

(+1.7%), remain slightly above zero in the second quintile (+0.10%), and turn negative in the third (−0.56%), reaching −1.96% in the fifth quintile. In other terms, in the bottom quintiles, where transfers represent a main income component, the positive effects of inflation adjustment overcome the negative variations in returns to labor and capital. On the contrary, the other quintiles experience a reduction in welfare. This is coherent with previous results in the literature. The uses-side effects, in the range of 8.6%−9.7%, indicate a negative welfare change and are subtracted from the sources-side effects to obtain the total effect (Eq. (8)). The overall welfare effect is negative, ranging from −7.2% in the bottom to −11.7% in the top quintile, and progressively distributed ($K = 0.07$).[46]

When we simulate the scenario with technological change (FF+CT +IF), shown in Table 9, sources-side impacts are positive for all quintiles. This positive effect is offset by the negative impacts on the uses-side for all quintiles: the overall welfare loss for the first quintile is −7.7% and reaches −8.2% in the top quintile. Also in this case, the welfare impacts are progressively distributed, but to a lower extent ($K = 0.02$).

[46] In this set of simulations, the capital income component includes imputed rents. The inclusion is motivated by the peculiar composition of capital income in Italy, as already noticed. Among households in the bottom decile, the low levels of other income sources (e.g., pensions) amplify the relative importance of capital income (financial wealth predominantly held in homeownership). Excluding this component entirely would imply, in our view, omitting a significant aspect of the analysis. Further, imputed rent can be alternatively seen as returns to investments in assets of equivalent value, which would be affected by introducing a climate policy, changing the relative return of liquid vs illiquid activities. However, we have performed a sensitivity analysis excluding imputed rents. The exclusion does not significantly change the results either qualitatively or qualitatively. The only significant change is that the sign of sources-side effects changes at the fourth instead of the third quintile. Specifically, excluding imputed rents, sources-side welfare effects remain positive in the first quintile (+2.8%), are slightly above zero in the second quintile (+1.00%), and turn negative in the fourth (−0.35%) instead of the third quintile, reaching −1.13% in the fifth quintile. In other terms, it is confirmed that in the bottom quintiles, where transfers represent a main income component, the positive effects of inflation adjustment after the climate policy overcome the negative variations in returns to labor and capital. On the contrary, the other quintiles still experience a reduction in welfare. After excluding the imputed rents, the uses-side effects are in the range of 8.7%–9.82% and confirm the negative welfare change after the price changes induced by the policy. Subtracting the uses-side effects from the sources-side ones, the overall welfare effect is negative, ranging from - 6.2% in the bottom quintile to −10.96% in the top quintile. Further details are available from the authors upon request.

Overall, the sign of the effect of the simulated climate mitigation policy on returns to production factors depends on whether revenues are reinvested in clean energy technologies. With and without reinvestment, the Kakwani indexes for the distribution of sources-side effects are higher than the ones for the uses-side effects. This implies that sources-side effects reinforce the progressivity of the impacts on the uses-side, especially in the scenario without technological change. This contrasts with previous studies for the US, where uses-side effects are regressive and are counterbalanced by the progressivity of the sources-side effects (Fullerton et al., 2012; Goulder et al., 2019; Williams III et al., 2015).

7. Discussion and final remarks

In this work, we provide an *ex-ante* evaluation of the distributional effects of climate policies coherent with the European Green Deal applied to the Italian case. Specifically, we examine a policy mix in line with the goal of the Fit for 55 package adopted by the European Commission in 2021. Starting from the macroeconomic evaluation of different policy scenarios developed by Antimiani et al. (2023), we use CGE simulations to calculate the price changes induced by the policy mix, including the phase-out of fossil fuel subsidies and the introduction of a carbon tax. Then, we estimate a complete demand system, coherent with the microeconomic consumer theory, deriving the demand parameters for our welfare analysis. The demand parameter estimations from the micro model and price changes from the macro model are used to calculate the simulated uses-side welfare impacts of the policy. This soft-linking estimation method allows for disentangling the welfare effects of price changes in energy and non-energy product categories for households in different expenditure quintiles, evaluating the direct, indirect, and demand-side effects of the price changes.

Our results detect a welfare loss for households at all levels of the expenditure distribution. The value of the loss increases when we move up the expenditure distribution, suggesting an overall progressive effect. In other words, our results do not support the presumption, generally widespread in public opinion and political debate, that the poorest groups in the population bear the burden of climate policies the most. We have also shown that our distributional result is strictly linked to the inclusion of demand-side adjustments in the analysis: neglecting the substitution possibilities households may have in reaction to price increases at different expenditure levels may lead to a completely different distributional scenario. Disentangling the contribution of different price changes to the overall welfare impact, our analysis reveals a regressivity profile for the food price increase, which is particularly large, suggesting the need for policy-makers to complement the implementation of climate policies with well-defined and precise redistributive

Table 9
Source and use-side welfare effects (FF+CT+IF, EV in euro\month).

	EV source	Burden (%)	-EV Use	Burden (%)	Total	Burden (%)
First quintile	6.365	1.188	−46.233	−8.889	−39.868	−7.702
	(0.04)	(0.00)	(0.93)	(0.16)	(0.92)	(0.16)
Second quintile	14.380	1.513	−83.017	−8.772	−68.637	−7.259
	(0.04)	(0.00)	(1.60)	(0.17)	(1.60)	(0.17)
Third quintile	21.904	1.611	−125.963	−9.299	−104.059	−7.687
	(0.04)	(0.00)	(2.23)	(0.16)	(2.23)	(0.16)
Fourth Quintile	34.116	1.800	−184.431	−9.756	−150.315	−7.956
	(0.08)	(0.00)	(3.04)	(0.16)	(3.03)	(0.16)
Fifth quintile	55.508	1.929	−292.738	−10.130	−237.230	−8.201
	(0.17)	(0.00)	(4.44)	(0.15)	(4.40)	(0.15)
K	0.061		0.028		0.021	
	(0.0003)		(0.004)		(0.005)	

Note: For each quintile the equivalent variation for the sources-side impacts ($EV\ Source$), for the uses-side impacts ($EV\ Use$), and the total welfare impacts ($Total$) of the simulated policy are reported, together with the respective burden. The climate policy includes the removal of Fossil Fuel subsidies and the introduction of the Carbon Tax ($FF + CT$)). The bottom line reports the Kakwani index (K).

interventions. Further, the analysis of the price elasticities for different good categories highlights different patterns across the expenditure distribution, confirming that poor and rich households do not have the same substitution opportunities in several cases.

Our work contributes to the literature by also considering the potential impact of climate policy on the sources-side. Using factor price changes derived from the CGE model, our simulation exercise reveals that a crucial assumption driving the welfare impacts is related to the potential use of the revenue generated by the policy to finance investments in clean energy technologies in the spirit of the Innovation Fund. When this revenue recycling complements the simulated climate policy (CT+FF), we find that the sources-side impacts turn from negative to positive for all income quintiles. With or without investments, however, the distributional impacts on the sources-side are strongly progressive and reinforce the mildly progressive impacts on the uses-side.

Our empirical analysis suffers from some limitations, mainly related to data availability. The limited variability in price indices, which are available only at the regional level for Italy, may create problems of weak identification of the demand system.

Another limitation relates to the assumption we make when introducing technological change through the Innovation Fund mechanism. In the soft-linking approach, we assume that higher wages equally benefit all workers and workers only. This is due to some restrictive assumptions of the labor market in the GDynEP model, such as full employment, no barriers in the transition from unskilled to skilled competencies, and neutral technical change. This automatically brings the result that additional labor demand could benefit lower-income groups by increasing salaries, disregarding potential market failures.

Despite these limitations, our work may contribute to the current debate on the socio-economic and distributional effects of climate-related mitigation actions that are the basis for the EU Just Transition policy. We provide some suggestions on evaluating the distributional impacts of these interventions to have the informative basis for designing compensating measures to support the introduction of policies coherent with the climate objectives, differentiating the incentive measures by household types and energy consumption profile.

CRediT authorship contribution statement

Valeria Costantini: Supervision, Funding acquisition, Conceptualization. **Chiara Martini:** Writing – review & editing. **Benedetta Mina:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Mariangela Zoli:** Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization.

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Appendix A. Demand system

A.1. Quadratic almost ideal demand system

The indirect utility function is defined as:

$$\ln V(\mathbf{p}, m) = \left[\left(\frac{\ln m - \ln a(\mathbf{p})}{b(\mathbf{p})} \right)^{-1} + \lambda(\mathbf{p}) \right]^{-1} \tag{A.1}$$

where m is the nominal level of total expenditure and $\mathbf{p}$ is a vector of price indices, entering the following equations:

$$\ln a(\mathbf{p}) = \alpha^0 + \sum_{i=1}^{K} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{K} \sum_{j=1}^{K} \gamma_{ij} \ln p_i \ln p_j \tag{A.2}$$

$$b(\mathbf{p}) = \prod_{i=1}^{K} p_i^{\beta_i} \qquad \lambda(\mathbf{p}) = \sum_{i=1}^{K} \lambda_i \ln p_i \tag{A.3}$$

where $k = 1...K$ are goods included in the systems and α^0 is chosen to be just below the lowest value of $\ln m$. Demand functions are obtained by applying Roy's identity to the indirect utility function as in Eq. (A.1).

$$x_i(\mathbf{p}, m) = -\left(\frac{\partial V(\mathbf{p}, m)}{\partial \mathbf{p}} \Big/ \frac{\partial V(\mathbf{p}, m)}{\partial m} \right) \tag{A.4}$$

$$w_i = \alpha_i + \sum_{j=1}^{K} \gamma_{ij} \ln p_j + \beta_i \ln \left[\frac{m}{a(\mathbf{p})} \right] + \frac{\lambda_i}{b(\mathbf{p})} \left\{ \ln \left[\frac{m}{a(\mathbf{p})} \right] \right\}^2 \tag{A.5}$$

where $w_i = \frac{x_i}{m}$.

The linearity of the budget constraint and rational choice axioms impose the following requirements. Adding-up:

$$\sum_{i=1}^{K} \alpha_i = 1 \qquad \sum_{i=1}^{K} \beta_i = \sum_{i=1}^{K} \lambda_i = 0 \tag{A.6}$$

Homogeneity:

$$\sum_{j=1}^{K} \gamma_{ij} = 0 \tag{A.7}$$

Symmetry:

$$\gamma_{ij} = \gamma_{ji} \tag{A.8}$$

for all $i \neq j$. To find the cost function we have to invert the indirect utility function. First, we write the indirect utility in a way that is directly related to AIDS:

$$\ln V = \ln\left[\frac{m}{a(\mathbf{p})}\right] \Big/ \left\{ b(\mathbf{p}) + \lambda(\mathbf{p}) \ln\left[\frac{m}{a(\mathbf{p})}\right] \right\} \tag{A.9}$$

Isolating $\ln m$ from Eq. (A.9) we have an expression for the logarithmic cost function in QUAIDS:

$$\ln m(V, \mathbf{p}) = \ln a(\mathbf{p}) + \frac{\ln V(\mathbf{p}, m) b(\mathbf{p})}{1 - \lambda(\mathbf{p}) \ln V(\mathbf{p}, m)} \tag{A.10}$$

that is used in welfare measures.

The demographic-augmented version of the QUAIDS assumes that the cost function of a reference household ($m^R(\mathbf{p}, u)$) is scaled by another function ($g_0(\mathbf{p}, \mathbf{z}, u)$):

$$m(\mathbf{p}, \mathbf{z}, u) = g_0(\mathbf{p}, \mathbf{z}, u) * m^R(\mathbf{p}, u) \tag{A.11}$$

The scaling function ($g_0(\mathbf{p}), \mathbf{z}, u)$) is made of two elements:

$$g_0(\mathbf{p}, \mathbf{z}, u) = \bar{g}_0(\mathbf{z}) \phi(\mathbf{p}, \mathbf{z}, u) \tag{A.12}$$

The first element ($\bar{g}_0(\mathbf{z})$ depends only on demographic variables ($\mathbf{z}$):

$$\bar{g}_0(\mathbf{z}) = 1 + \rho' \mathbf{z} \tag{A.13}$$

The second element depends also on the utility levels and changes in prices:

$$\ln \phi(\mathbf{p}, \mathbf{z}, u) = \frac{\prod_{i=1}^{K} p_i^{\beta_i} (\prod_{i=1}^{K} p_i^{\eta_i' z} - 1)}{\frac{1}{u} - \sum_{i=1}^{K} \lambda_i \ln p_i} \tag{A.14}$$

That yields the following form for demand equations:

$$w_i = \alpha_i + \sum_{j=1}^{K} \gamma_{ij} \ln p_j + (\beta_i + \eta_i z) \ln\left[\frac{m}{\bar{g}_0(\mathbf{z}) a(\mathbf{p})}\right] + \frac{\lambda_i}{b(\mathbf{p}) c(\mathbf{p}, \mathbf{z})} \left\{ \ln\left[\frac{m}{\bar{g}_0(\mathbf{z}) a(\mathbf{p})}\right] \right\}^2 \tag{A.15}$$

where

$$c(\mathbf{p}, \mathbf{z}) = \prod_{i=1}^{K} p_i^{\eta_i' z} \tag{A.16}$$

A.2. Welfare measure

The compensating variation is defined as:

$$CV = c(u^0, \mathbf{p}^1) - c(u^0, \mathbf{p}^0) \tag{A.17}$$

where $c(u, \mathbf{p})$ are cost functions. We only have an expression for QUAIDS logarithmic cost functions, that is why we have to resort to True Cost of Living Indices (TCOL). The TCOL associated to the compensating variation is:

$$TCOL = \frac{c(u^0, \mathbf{p}^1)}{c(u^0, \mathbf{p}^0)} \tag{A.18}$$

$$\ln TCOL = \ln\left[\frac{c(u^0, \mathbf{p}^1)}{c(u^0, \mathbf{p}^0)}\right] \tag{A.19}$$

$$\ln TCOL = \ln c(u^0, \mathbf{p}^1) - \ln c(u^0, \mathbf{p}^0) \tag{A.20}$$

We obtain an expression for $\ln TCOL$ from logarithmic cost functions (Eq. (A.10). Then we take the exponential and combine the TCOL with a reference level of expenditure to obtain the welfare change:

$$CV = c(u^0, \mathbf{p}^0)(TCOL - 1) \tag{A.21}$$

Using QUAIDS notation:

$$\ln TCOL = \ln m(V^0, \mathbf{p}^1) - \ln m(V^0, \mathbf{p}^0) \tag{A.22}$$

Assuming a unitary vector of prices at the initial time $p^0 = 1 \ \forall i$, equations [(A.2)], [(A.3)] are:

$$\ln a(\mathbf{p}) = \alpha^0 \qquad b(\mathbf{p}) = 1 \qquad \lambda(\mathbf{p}) = 0 \tag{A.23}$$

implying from [(A.9)] and [(A.10)]:

$$\ln V^0 = \ln m^0 - \alpha^0 \tag{A.24}$$

$$\ln m(V^0, \mathbf{p}^0) = \ln m^0 \tag{A.25}$$

The first term of (A.22) is:

$$\ln m(V^0, \mathbf{p}^1) = \ln a(\mathbf{p}^1) + \frac{\ln V^0 b(\mathbf{p}^1)}{1 - \lambda(\mathbf{p}^1) \ln V^0} \tag{A.26}$$

$$\ln m(V^0, \mathbf{p}^1) = \ln a(\mathbf{p}^1) + \frac{(\ln m^0 - \alpha^0) b(\mathbf{p}^1)}{1 - \lambda(\mathbf{p}^1)(\ln m^0 - \alpha^0)} \tag{A.27}$$

The logarithm of the TCOL for the compensating variation is:

$$\ln TCOL = \ln a(\mathbf{p}^1) + \frac{(\ln m^0 - \alpha^0) b(\mathbf{p}^1)}{1 - \lambda(\mathbf{p}^1)(\ln m^0 - \alpha^0)} - \ln m^0 \tag{A.28}$$

expressed with the demand system parameters:

$$\ln TCOL = \alpha^0 + \sum_{i=1}^{K} \alpha_i \ln p_i^1 + \frac{1}{2} \sum_{i=1}^{K} \sum_{j=1}^{K} \gamma_{ij} \ln p_i^1 \ln p_j^1 + \frac{(\ln m^0 - \alpha^0) \prod_{i=1}^{K} p_i^{1\beta_i}}{1 - \sum_{i=1}^{K} \lambda_i \ln p_i^1 (\ln m^0 - \alpha^0)} - \ln m^0 \tag{A.29}$$

Using the demographic-augmented QUAIDS, the corresponding TCOL is:

$$\ln TCOL = \alpha^0 + \sum_{i=1}^{K} \alpha_i \ln p_i^1 + \frac{1}{2} \sum_{i=1}^{K} \sum_{j=1}^{K} \gamma_{ij} \ln p_i^1 \ln p_j^1 + \ln(1 + \rho' z) + \tag{A.30}$$

$$+ \frac{(\ln m^0 - \alpha^0 - \ln(1 + \rho' z)) \prod_{i=1}^{K} p_i^{1\beta_i} \prod_{i=1}^{K} p_i^{\eta_i' z}}{1 - \sum_{i=1}^{K} \lambda_i \ln p_i^1 (\ln m^0 - \alpha^0 - \ln(1 + \rho' z))} - \ln m^0 \tag{A.31}$$

A.3. Engel curves

See Figs. A.1 and A.2.

Appendix B. Data

See Figs. B.1–B.3.

Appendix C. Estimation

See Tables C.1–C.12.

Appendix D. Welfare analysis

D.1. QUAIDS-GTAP mapping

See Table D.1.

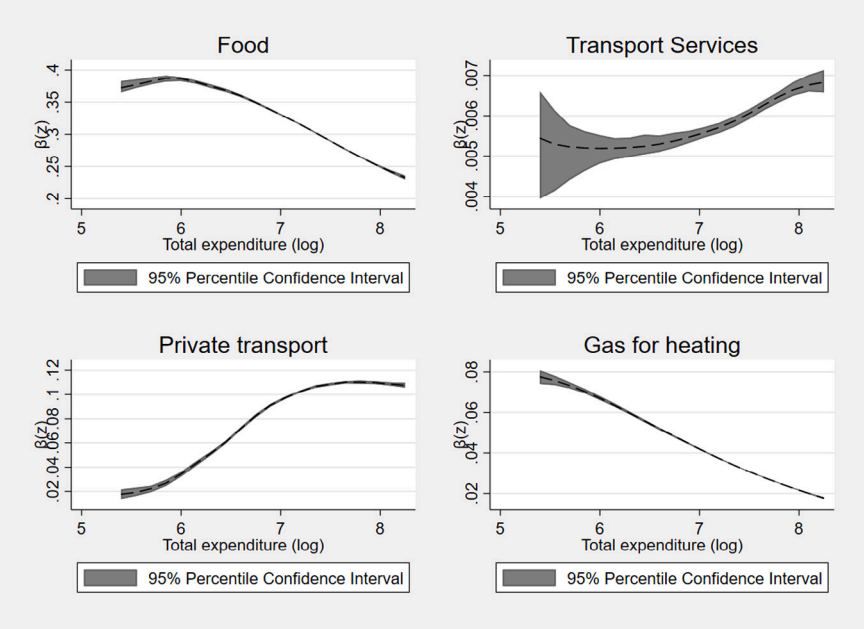

Fig. A.1. Semi-parametric Engel Curves. Note: Own elaboration on the Italian Household Budget Survey (Istat) 2014–2020, $N = 116,195$.

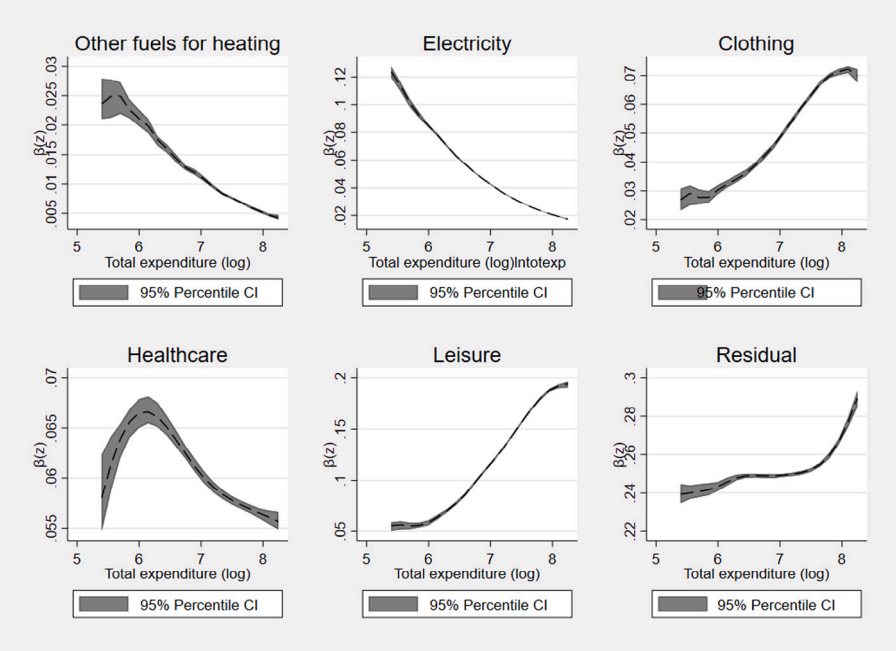

Fig. A.2. Semi-parametric Engel Curves. Note: Own elaboration on the Italian Household Budget Survey (Istat) 2014–2020, $N = 116,195$.

Table C.1
Demand function parameters (Eq. (A.15)).

	Food	Public t.	Private t.	Gas	Heat	Elect	Clothing	Health	Leisure	Other
α	0.286	0.096	0.018	0.044	0.079	0.104	0.035	0.019	0.023	0.159
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
β	.063	−.058	.010	−.017	−.043	−.035	−.002	.015	.024	.024
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
λ	−.029	.009	.008	.003	.007	.002	.0026	−.0001	.005	−.005
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.144	0.000	0.000
δ	.442	.002	.075	.030	.016	.136	.064	.064	.092	.309
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

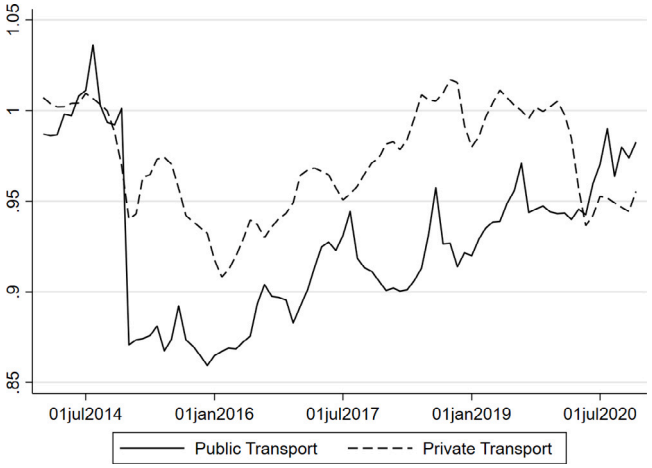

Fig. B.1. Transport price indices trends.
Note: Own elaboration on Istat data, 2014–2020.

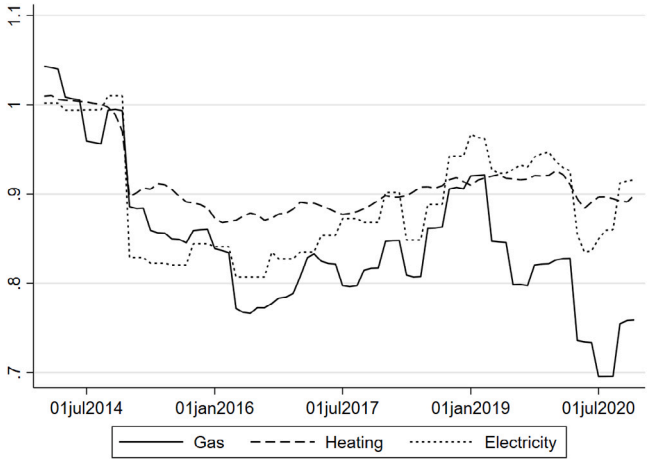

Fig. B.2. Domestic energy price indices trends.
Note: Own elaboration on Istat data, 2014–2020.

Table C.2
Demand function parameters (Eq. (A.13)).

	hhsize	location	agehead
ρ	−.021	.080	−.002
p-val	0.000	0.000	0.000

D.2. Price vectors for the simulation

The GDynEP model yields price variations in percentage points for 36 commodity sectors between 2020 and 2030 for policy scenarios and the business-as-usual scenario (BAU). The model does not provide price

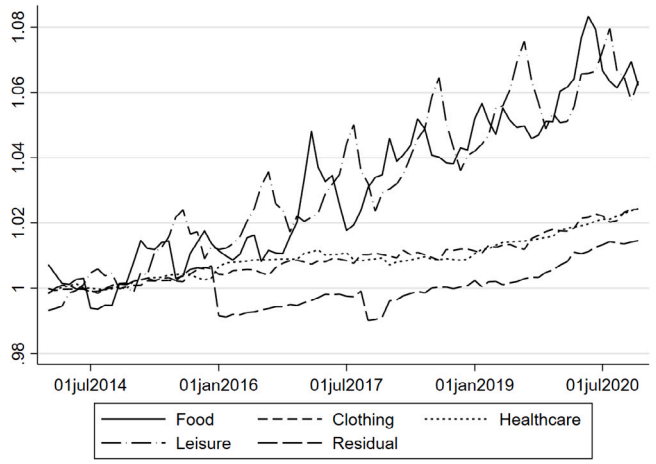

Fig. B.3. Other goods price indices trends.
Note: Own elaboration on Istat data, 2014–2020.

levels. We are not using directly price variations (%) but differences in percentage points price variations between policy scenarios (where the carbon price CP corresponds to the simultaneous implementation of a carbon tax and the removal of fossil fuels subsidies)[47] and BAU reported in . Each entry in can be expressed as:

$$\Delta p^{2030CP} = p^{2030CP} - p^{2030BAU} \tag{D.1}$$

where p^{2030CP} is the percentage point price variation (2020–2030) under the policy scenario for one of the 36 GTAP commodities and $p^{2030BAU}$ expresses the price variation over the same time span, had there not been the climate policy. For simplicity, we drop the commodity indicators. Expressed in price levels, that are not provided by GTAP:

$$p^{2030CP} = \frac{P^{2030CP} - P^{2020}}{P^{2020}} \tag{D.2}$$

$$p^{2030BAU} = \frac{P^{2030BAU} - P^{2020}}{P^{2020}} \tag{D.3}$$

This is to clarify that in GDynEP all price variations and differences are expressed with respect to 2020 price levels (P^{2020}). If we want to express the table elements in terms of price levels we thus have:

$$\Delta p^{2030CP} = p^{2030CP} - p^{2030BAU} = \frac{P^{2030CP} - P^{2030BAU}}{P^{2020}} \tag{D.4}$$

That is the price variation due to the policy-induced increase (or in a few cases decrease) with respect to BAU expressed over 2020 price levels. The 36 Δp^{2030} are then aggregated using GDynEP weights into

[47] The carbon price is also affected by the introduction of the Innovation Fund when the FF+CT+IF scenario is simulated, as the equilibrium carbon tax required for achieving the emission abatement target is lower.

Table C.3
Demand function parameters (Eq. (A.15)).

η	Food	Public t.	Private t.	Gas	Heat	Elect	Clothing	Health	Leisure	Other
hhsize	.0023062	−.0001104	.0002417	.0002274	.0002822	.0006596	.0005394	−.0013526	−.0006015	−.002192
location	−.000414	2.69e−06	−.0002681	.0006763	−.0000739	−.000678	.0001738	.0002609	.002494	−.0021735
agehead	.0000348	−.0000105	−.0001672	−4.53e−06	−3.46e−07	−.0000589	−.0000746	−9.82e−06	−.000085	.0003761

Table C.4
Demand function parameters (Eq. (A.15)).

γ	Food	Public t.	Private t.	Gas	Heat	Elect	Clothing	Health	Leisure	Other
r1	.1998029	.0196081	−.0330814	−.030531	−.0013026	.0673115	−.0412598	−.0113452	−.0040609	−.1651416
r2	.0196081	−.0038574	−.0017625	−.0051788	.0038945	−.0071343	.0158499	−.0350155	−.0062156	.0198117
r3	−.0330814	−.0017625	.0337529	−.0061247	−.0026283	−.0031028	.007343	.0310266	−.0383081	.0128853
r4	−.030531	−.0051788	−.0061247	−.008135	.0092809	.0221111	.0221921	−.0098804	.0207968	−.0145309
r5	−.0013026	.0038945	−.0026283	.0092809	−.0104477	.0001337	−.0106961	.0226584	.0067651	−.0176579
r6	.0673115	−.0071343	−.0031028	.0221111	.0001337	−.0186627	−.0180223	.0046332	−.0120438	−.0352236
r7	−.0412598	.0158499	.007343	.0221921	−.0106961	−.0180223	−.0395826	.0517051	.0022131	.0102574
r8	−.0113452	−.0350155	.0310266	−.0098804	.0226584	.0046332	.0517051	−.0020992	−.0167947	−.0348883
r9	−.0040609	−.0062156	−.0383081	.0207968	.0067651	−.0120438	.0022131	−.0167947	.0570628	−.0094148
r10	−.1651416	.0198117	.0128853	−.0145309	−.0176579	−.0352236	.0102574	−.0348883	−.0094148	.2339026

Table C.5
Uncompensated elasticities.

e_{ij}	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
Food	−0.339	0.091	0.051	−0.088	−0.018	0.093	0.004	0.194	−0.098	−0.166
pubtr	1.225	−1.721	0.062	−0.257	1.614	−0.609	3.122	−7.637	0.419	2.807
privatet	−0.763	−0.027	−0.600	−0.059	−0.071	−0.085	0.120	0.541	−0.700	−0.169
Gas	−2.485	−0.769	−0.851	−1.845	0.790	1.757	2.674	−0.180	0.813	−2.425
Heat	0.064	0.467	0.003	0.766	−1.500	−0.144	−1.022	2.139	0.154	−0.519
Elect	1.599	0.156	−0.107	0.362	0.113	−1.267	0.679	−1.883	−0.479	−1.672
Clothing	−1.184	0.172	0.336	0.242	−0.111	−0.270	−1.632	0.780	−0.087	0.126
Health	−0.278	−0.567	0.415	−0.164	0.309	0.103	0.573	−0.857	−0.234	−0.461
Leisure	−0.464	−0.015	−0.197	0.227	0.019	−0.205	0.046	0.075	−0.478	−0.008
Other	−0.367	−0.003	0.049	0.034	−0.056	−0.110	0.104	−0.154	−0.001	−0.526

Table C.6
Compensated elasticities.

	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
Food	−0.099	0.094	0.110	−0.074	−0.009	0.130	0.040	0.237	−0.004	0.021
pubtr	1.168	−1.721	0.048	−0.260	1.612	−0.618	3.114	−7.647	0.396	2.763
privatet	−0.236	−0.021	−0.469	−0.028	−0.050	−0.005	0.199	0.635	−0.492	0.241
Gas	−2.125	−0.764	−0.762	−1.824	0.804	1.812	2.728	−0.116	0.955	−2.145
Heat	0.270	0.469	0.054	0.778	−1.492	−0.113	−0.991	2.176	0.236	−0.358
Elect	1.684	0.157	−0.086	0.367	0.116	−1.254	0.692	−1.868	−0.446	−1.606
Clothing	−0.783	0.176	0.435	0.266	−0.096	−0.209	−1.571	0.851	0.071	0.438
Health	0.122	−0.562	0.515	−0.141	0.325	0.163	0.633	−0.785	−0.076	−0.150
Leisure	0.012	−0.009	−0.079	0.255	0.038	−0.132	0.118	0.160	−0.290	0.361
Other	−0.046	0.001	0.129	0.053	−0.043	−0.061	0.152	−0.097	0.126	−0.276

Table C.7
Compensated elasticities — first quintile.

	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
Food	−0.159	0.072	0.030	−0.053	0.010	0.185	−0.007	0.112	0.036	−0.038
pubtr	0.613	−1.241	0.035	−0.065	0.444	−0.154	0.894	−2.128	0.203	0.932
privatet	−0.273	−0.019	−0.418	−0.043	−0.055	0.018	0.217	0.740	−0.693	0.241
Gas	−3.729	−1.676	−1.694	−2.605	1.353	3.029	5.354	0.266	0.841	−4.834
Heat	0.537	0.374	0.161	0.732	−1.415	−0.337	−1.113	2.380	0.029	0.255
Elect	1.173	0.051	−0.024	0.256	0.069	−1.127	0.208	−0.669	−0.184	−0.636
Clothing	−0.790	0.167	0.433	0.243	−0.075	−0.173	−1.568	0.821	0.004	0.428
Health	0.001	−0.808	0.544	−0.218	0.420	0.354	0.437	−0.365	−0.152	−0.108
Leisure	0.364	−0.062	−0.255	0.194	0.063	−0.034	0.068	−0.079	−0.407	0.203
Other	0.001	0.005	0.104	0.063	−0.035	−0.037	0.156	−0.112	0.090	−0.297

10 sub-commodities groups corresponding to QUAIDS resulting in 10 price differences reported in .

To build the policy price indices vectors we sum Δp^{2030CP} to ISTAT price indices for 2019. ISTAT price indices for 2019 are expressed in levels as:

$$p^{2019} = \frac{P^{2019}}{P^{2014}} \tag{D.5}$$

So we build a vector:

$$p^{2019CP} = p^{2019} + \Delta p^{2030CP} = \frac{P^{2019}}{P^{2014}} + \frac{P^{2030CP} - P^{2030BAU}}{P^{2020}} \tag{D.6}$$

The simulations thus provide the welfare effects as if in 2019 prices had registered an additional variation due to climate policies equal to that simulated in GDynEP for the 5-year span 2020–2030. The

Table C.8
Compensated elasticities — second quintile.

	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
food	−0.128	0.928	−0.319	−2.653	0.368	1.499	−0.699	0.108	0.190	−0.016
pubtr	0.082	−1.489	−0.024	−1.057	0.434	0.125	0.185	−0.614	−0.037	−0.002
privatet	0.076	0.031	−0.415	−1.064	0.083	−0.064	0.393	0.518	−0.150	0.120
gas	−0.065	−0.170	−0.033	−2.078	0.762	0.322	0.275	−0.157	0.214	0.060
heat	−0.002	1.007	−0.065	0.985	−1.472	0.100	−0.099	0.345	0.046	−0.041
elect	0.151	−0.395	−0.005	2.217	−0.187	−1.210	−0.201	0.204	−0.083	−0.052
Clothing	0.019	1.985	0.228	3.575	−1.032	0.552	−1.568	0.598	0.092	0.156
health	0.182	−4.847	0.759	−0.005	2.240	−1.503	0.843	−0.704	0.044	−0.103
leisure	0.019	0.285	−0.654	0.937	0.167	−0.184	0.066	−0.098	−0.365	0.115
other	−0.005	1.837	0.201	−3.004	−0.164	−1.292	0.434	−0.143	0.286	−0.302

Table C.9
Compensated elasticities — third quintile.

	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
Food	−0.093	0.094	0.113	−0.075	−0.009	0.129	0.041	0.240	−0.004	0.017
pubtr	1.228	−1.746	0.048	−0.281	1.721	−0.656	3.316	−8.135	0.392	2.938
privatet	−0.260	−0.021	−0.457	−0.027	−0.053	−0.008	0.206	0.656	−0.507	0.228
Gas	−1.963	−0.676	−0.672	−1.748	0.750	1.691	2.474	−0.148	0.957	−1.889
Heat	0.220	0.458	0.028	0.735	−1.474	−0.050	−0.891	1.978	0.270	−0.456
Elect	1.740	0.175	−0.095	0.375	0.123	−1.265	0.770	−2.049	−0.482	−1.737
Clothing	−0.732	0.183	0.413	0.275	−0.101	−0.211	−1.564	0.847	0.086	0.434
Health	0.136	−0.538	0.514	−0.133	0.318	0.145	0.659	−0.830	−0.071	−0.158
Leisure	0.047	−0.015	−0.080	0.239	0.038	−0.120	0.112	0.134	−0.316	0.342
Other	−0.043	−0.002	0.133	0.057	−0.043	−0.062	0.156	−0.099	0.129	−0.290

Table C.10
Compensated elasticities — fourth quintile.

	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
Food	−0.044	0.109	0.150	−0.086	−0.017	0.109	0.064	0.304	−0.034	0.039
pubtr	1.384	−1.929	0.117	−0.373	2.477	−0.884	4.659	−11.392	0.516	4.047
privatet	−0.208	−0.016	−0.497	−0.020	−0.040	−0.009	0.185	0.558	−0.371	0.249
Gas	−1.363	−0.354	−0.336	−1.464	0.544	1.228	1.536	−0.254	0.952	−0.949
Heat	0.071	0.466	−0.008	0.680	−1.447	0.076	−0.723	1.661	0.359	−0.677
Elect	2.019	0.230	−0.134	0.437	0.150	−1.326	1.001	−2.639	−0.624	−2.226
Clothing	−0.818	0.172	0.460	0.261	−0.093	−0.215	−1.556	0.842	0.094	0.434
Health	0.139	−0.492	0.517	−0.118	0.301	0.110	0.690	−0.901	−0.048	−0.167
Leisure	−0.099	0.007	−0.015	0.268	0.033	−0.157	0.133	0.221	−0.258	0.395
Other	−0.070	−0.002	0.145	0.056	−0.045	−0.070	0.159	−0.097	0.143	−0.284

Table C.11
Compensated elasticities — fifth quintile.

	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
Food	0.061	0.134	0.203	−0.107	−0.030	0.082	0.099	0.409	−0.091	0.067
pubtr	0.853	−1.712	0.287	−0.283	2.406	−0.752	4.369	−10.519	0.615	3.758
privatet	−0.168	−0.008	−0.537	−0.011	−0.025	−0.010	0.165	0.453	−0.222	0.265
Gas	−0.811	−0.059	−0.018	−1.198	0.350	0.780	0.677	−0.329	0.925	−0.098
Heat	−0.117	0.445	−0.020	0.567	−1.368	0.212	−0.464	1.175	0.452	−0.841
Elect	2.549	0.325	−0.213	0.555	0.200	−1.433	1.393	−3.666	−0.890	−3.096
Clothing	−0.788	0.171	0.456	0.259	−0.089	−0.214	−1.520	0.810	0.131	0.420
Health	0.123	−0.449	0.524	−0.104	0.286	0.077	0.712	−0.958	−0.018	−0.172
Leisure	−0.230	0.026	0.054	0.284	0.030	−0.184	0.150	0.285	−0.221	0.429
Other	−0.150	0.013	0.163	0.035	−0.048	−0.084	0.145	−0.085	0.157	−0.198

Table C.12
Expenditure elasticities by quintile.

Quintile	Food	pubtr	privatet	Gas	Heat	Elect	Clothing	Health	Leisure	Other
Q1	0.91	−0.04	1.52	0.98	0.41	0.53	1.14	1.34	1.36	1.01
Q2	0.79	−0.28	1.63	1.04	0.49	0.35	1.17	1.23	1.40	0.98
Q3	0.71	−0.10	1.61	1.09	0.65	0.22	1.20	1.19	1.42	0.96
Q4	0.62	0.76	1.56	1.13	0.84	0.09	1.24	1.17	1.44	0.95
Q5	0.47	2.33	1.51	1.18	1.14	−0.17	1.25	1.14	1.45	0.95

Table D.1
QUAIDS-GTAP mapping.

QUAIDS	ECOICOP	N. GTAP sector	Description GTAP sector
Food	01 Food and non-alcoholic beverages	1	Rice
		2	Cereal grains
		3	Other primary
		4	Vegetable and fruit
		5	Livestock
		6	Rumin meat
		7	Other meat
		8	Fishery
		9	Dairy
		11	Processed food
		12	Sugar
Public transport	07.3 Transport services (excl. air)	32	Road and railway transport
		34	Water transport
Private Transport	07.2 Operation of personal transport equipment	31	Oil products
Gas	04.5.2 Gas	28	Natural gas and LNG
Other heating fuels	04.5.3 Liquid fuels, 04.5.4 Solid fuels	26	Coal
		27	Oil crude
Electricity	04.5.1 Electricity	29	Electricity from fossil fuels
		30	Electricity from renewables
Clothing	03 Clothing and footwear	13	Textile
		3	Other primary
		35	Service private
Healthcare	06 Health	17	Pharmaceutics
Leisure	02, 09, 11	10	Beverages and tobacco
		14	Paper and publishing
		35	Service private
		36	Service public
Residual	04.3, 04.4, 05, 08, 10, 12	14	Paper and publishing
		15	Wood
		16	Chemical
		18	Mineral
		19	Motor vehicles
		20	Transport equipment
		21	Electronics and elect equip
		22	Metal product
		23	Machinery
		24	Ferrous metal
		25	Other manufacturing
		35	Service private
		36	Service public

counterfactual is the welfare variation corresponding to the observed price vector p^{2019}.[48]

Appendix E. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108181.

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