Geography versus Income: The Heterogeneous Effects of Carbon Taxation*

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Abstract

The distributive effects of carbon taxation are critical for its political acceptability and depend on both income and geographic factors. Using French administrative data, household surveys, and matched employer-employee records, we document that rural households spend 2.8 times more on fossil fuels than urban households and work in firms that emit 2.7 times more greenhouse gases. We incorporate these facts into a spatial heterogeneous-agent model with migration, housing and wealth accumulation, bridging spatial and macroeconomic approaches. Carbon taxes generate 56% larger welfare losses for rural households than for urban households. While uniform or income-based rebates reduce inequality along the income dimension, they leave large spatial disparities that must be offset through location-based transfers. These results suggest that carbon policies should account for spatial differences to improve political feasibility.

JEL classification – C61, E62, H23, Q43, Q58, R13.

Keywords – Carbon tax, inequalities, revenue recycling, spatial and macroeconomic models, migration.

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Introduction

Carbon taxes reduce emissions but impose unequal costs for households and firms. Fossil fuels represent a larger share of expenditures for low-income and rural households, and a larger share of firms' input costs in rural areas. These distributive effects can undermine the political acceptability of carbon taxation, as illustrated in France by the Yellow Vests protests and the subsequent carbon tax freeze. Consequently, designing socially acceptable carbon taxes requires careful consideration of their distributional impacts on both households and firms. While the existing literature has predominantly focused on the "rich versus poor" dimension of the energy transition burden, less attention has been given to geographical heterogeneity in emission patterns. This paper addresses this gap by providing detailed empirical evidence on regional disparities and integrating these patterns into a rich quantitative model.

In the first part of the paper, we systematically document the distribution of direct emissions across both households and firms, using several datasets covering the French economy. We combine household-level survey data with fiscal declarations to estimate fossil fuel consumption for heating and transportation at a highly granular level. We derive worker-level emission patterns by linking matched employer-employee administrative data with sector-level greenhouse gas (GHG) emissions. In both the household and firm cases, we document how direct emissions vary across income levels and city sizes.

In the second part of the paper, we integrate these emission patterns into a spatial general-equilibrium heterogeneous-agent model that captures heterogeneity in both income and geography. Households endogenously decide whether to migrate in response to carbon taxation, taking into account mobility frictions and relocation incentives. The interaction between savings and migration costs allows households to accumulate resources in order to move and to smooth the adverse effects of the carbon tax, while borrowing constraints and homeownership limit mobility and give rise to "trapped" households. The model replicates the observed heterogeneity in income, wealth, housing status, and energy consumption across regions, as well as the cross-correlations between income, geography, and migration patterns. We then introduce carbon taxes on both households and firms and evaluate their distributive effects under different revenue-recycling scenarios, ranging from increased public spending to targeted transfers based on location and income. The paper delivers three main findings.

First, using micro data on households and firms, we show that there are strong spatial disparities in emission patterns. Household-level survey data reveal that rural households consume 2.8 times more fossil fuels, as a share of consumption, primarily due to larger homes and higher reliance on car travel. Additional evidence suggests that this rural-urban disparity in energy consumption extends beyond France, with similar patterns observed in the US, the UK, Germany, Spain, Italy, and the Netherlands. Moreover, by matching employer-employee records with sectoral-level emissions data, we find that rural workers are twice as likely as their urban counterparts to be employed in emissions-intensive sectors, such as agriculture and manufacturing. By attributing firm-level greenhouse gas emissions to employees based on firm size and sectoral emission intensity, we find that rural households are employed in firms that emit 2.7 times more GHGs than those employing Parisian households. We incorporate these findings into our spatial heterogeneous-agent model to examine the distributional effects of carbon taxation across both income and geographic dimensions.

Second, our quantitative model shows that carbon taxes disproportionately burden rural households, with effects varying across income levels, tax types, and housing status. In our benchmark policy scenario, targeting a 10% reduction in emissions, welfare losses in rural areas are 56% higher than those in Paris: -3.1% versus -2%, measured in consumption-equivalent terms. We decompose these effects by distinguishing between taxes on households' direct emissions and those on firms' emissions. The household tax is highly regressive, as fossil fuels are necessities and therefore disproportionately burden low-income households. The firm tax is less regressive: it primarily reduces wages, which adversely affects middle-income households, and lowers interest rates, thereby harming wealthier households. We also show that migration and mobility frictions, especially those related to homeownership, play a key role in shaping the distributive effects of carbon taxes. By allowing households, particularly renters, to relocate in response to changes in wages and housing costs, migration attenuates geographical inequalities and reduces the overall welfare cost of carbon taxation. In contrast, rural households, especially homeowners with illiquid housing wealth, can become effectively trapped in high-loss locations, generating pronounced spatial inequalities.

Third, we find that in the absence of location-specific rebates, rural households disproportionately bear the costs of the green transition. Redistributing carbon tax revenues through uniform or income-dependent lump-sum transfers substantially reduces inequality across income groups but fails to offset disparities across locations: rural households experience a -0.9% consumption-equivalent (CE) loss, while Parisian households experience a net 0.1% CE gain. Equalizing the burden of the carbon tax across both geographic and income dimensions requires location-specific transfers, which minimize maximum losses and reduce by half the standard deviation of welfare losses. In this location-specific transfer scenario, when households value emission reductions, carbon taxation can generate welfare gains for all households.

Our main contribution is to develop a unified general equilibrium framework to analyze the distributive effects of carbon taxation by jointly modeling households and firms while incorporating income, housing, and spatial dimensions. The framework bridges two strands of the literature: the *distributive effects of carbon taxation* and the *quantitative macro-spatial literature*.

The literature on the *distributive effects of carbon taxation* studies heterogeneous incidence using microsimulation, CGE, and heterogeneous-agent general equilibrium models. Microsimulation studies such as Cronin, Fullerton and Sexton (2019) for the United States or Douenne (2020) for France conclude that carbon taxes are regressive, with substantial heterogeneity within income quintiles. We confirm the regressive pattern but provide a structural explanation for within-quintile dispersion by introducing geography as an endogenous choice variable, making exposure to carbon taxation an equilibrium outcome rather than a fixed characteristic. Even with mobility, we show that spatial differences in energy requirements generate durable dispersion in tax burdens. Using CGE modelling, Rausch, Metcalf and Reilly (2011) and Goulder et al. (2019) demonstrate that progressive source-side effects can offset regressive use-side effects. Relative to these contributions, we endogenize both income and wealth distributions, and incorporate housing tenure and location choices within the canonical consumption–labor–savings problem. We further show that taxing households' direct emissions and taxing firms' emissions are not distributionally equivalent, as they operate through distinct general equilibrium channels and produce different incidence profiles. Finally, revenue recycling is central to the overall progressivity of carbon taxation. Consistent with Goulder et al. (2019) and Mathur and Morris (2014), we find that targeted transfers can substantially mitigate welfare losses and regressivity. However, income-based transfers alone fail to compensate rural households, motivating geography-based transfers. Unlike Fried, Novan and Peterman (2024), who study reductions in distortionary taxes, we focus on lump-sum rebates that keep carbon revenues separate from the general budget, a design that may enhance political acceptability.

This paper also contributes to the growing *quantitative macro-spatial literature* by embedding geography into a heterogeneous-agent general equilibrium model with energy use and climate policy. A growing strand of work building on Aiyagari (1994), studies the aggregate and distributional effects of energy shocks and carbon policies in incomplete-markets environments: Auclert, Monnery, et al. (2023); Pieroni (2023); Chan, Diz and Kanngiesser (2024); Kuhn and Schlattmann (2024); Bayer et al. (2026); Langot et al. (2026) or Ascari et al. (2026). We depart from this literature by explicitly modeling geographic heterogeneity in emissions for both households and firms, and by allowing for endogenous migration across regions. In doing so, we connect to the quantitative spatial literature on migration and worker reallocation in partial equilibrium, such as Desmet and Rossi-Hansberg (2014), Fajgelbaum et al. (2019) or Couture et al. (2024). Our contribution is to study how migration costs, homeownership, and borrowing constraints interact to generate gradual spatial reallocation in response to carbon taxation. Because we jointly model consumption–saving and location decisions, our paper is also related to quantitative frameworks that combine incomplete markets with spatial choice, such as Giannone et al. (2025); Greaney (2025) or

Greaney, Parkhomenko and Van Nieuwerburgh (2025). In the context of carbon taxation, we show how mobility frictions and local economic conditions produce gradual and uneven migration responses, with important implications for welfare and spatial inequality. Closest to our approach is Schlattmann (2024), who allows household energy requirements to vary by location. In comparison, we introduce endogenous savings, heterogeneous firm energy use across regions, and housing tenure choices which generate additional mobility frictions.

The remainder of the paper is organized as follows. Section 1 presents descriptive evidence on the distribution of greenhouse gas emissions across households and firms. Section 2 introduces the quantitative model. Section 3 discusses the calibration of the model using French data. Section 4 presents the main results, while Section 5 examines alternative rebate policies and Section 6 presents robustness checks. Finally, Section 7 concludes.

1 Descriptive Evidence

This section presents descriptive evidence on the distribution of greenhouse gas emissions by households and firms in France. First, rural households consume more energy and fossil fuels than urban households. Second, businesses in rural areas are more likely to operate in sectors with higher emissions. Although the focus is on France, we observe similar patterns in other countries.

1.1 Households' direct emissions

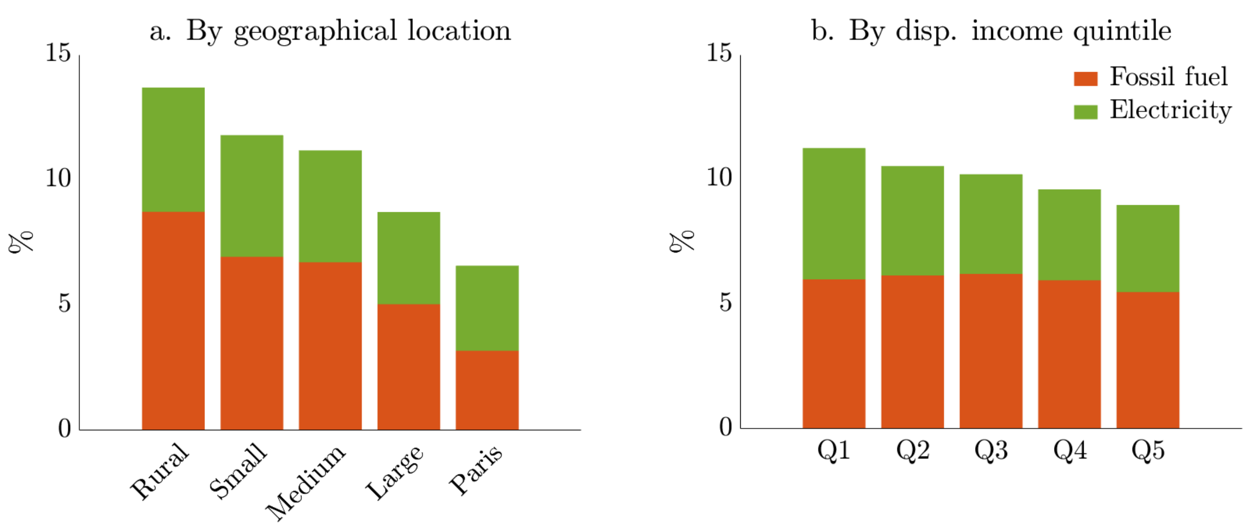
The direct cost of carbon taxes is borne by households with high consumption of carbon-intensive energy, such as fossil fuels. Since energy is typically a necessary good, most of the existing literature has focused on income disparities. However, using survey data from France, we find that the share of fossil fuels in total expenditures is relatively uniform across the income distribution, but declines significantly with the size of the city in which households reside.

Data. We use French microdata from the 2017 *Budget de Famille* (BdF) Insee survey, covering over 16,000 households. From this consumer expenditure survey, we construct household-level fossil fuel expenditures by adding up fuels for housing activities and those used in vehicles. Fossil-fuel consumption from transportation and heating make up more than 97% of households' direct emissions, while other activities are not identified in consumption surveys. Although electricity in France is largely carbon-neutral and therefore not affected by the carbon tax, we also compute the share of electricity in total expenditures to measure total energy use in each region and income group. This allows us to assess the importance of the overall energy constraint for each group, coming from transportation and housing needs.

Throughout the paper, we classify locations into five city types: Rural, Small cities, Medium cities, Large cities, and Paris, based on population size.[1] These categories respectively represent 23.5%, 26.0%, 18.5%, 13.4%, and 18.6% of the population. For a fair comparison, we also categorize households into five income groups, ranked by disposable income quintiles.

Empirical Results. We regress households' energy and fossil fuel expenditures on city type, income quintile, and control variables, as detailed in Appendix A.5. This approach helps control for potential correlation between income levels and location choices. The predicted shares of electricity and fossil fuel in total expenditures, by city type and income quintile, are shown in Figure 1. These shares can be interpreted as the average energy share in each city type (or each income quintile) if the city had the same characteristics as the whole population. While total energy is a necessary good — its share decreases from 11.3% for the first income quintile (Q1) to 8.9% for the fifth quintile (Q5) — the fossil fuel share remains flat across the income distribution, at approximately 5.9% of total expenditures. In contrast, geography strongly predicts energy consumption: rural households consume 2.1 times more energy than Parisians (13.7% versus 6.5%) and 2.8 times more fossil fuels (8.7% versus 3.1%). We then impute the fossil fuel share for all households in France using the complete set of fiscal declarations from households in 2021 as detailed in Appendix A.6. We present its spatial distribution in Figure 3, by averaging fossil fuel shares at the city code level.

Figure 1: Energy share in total consumption (regression-adjusted)



Notes. Mean share of fossil fuel and electricity in total consumption expenditures, net of controls, using survey weights (details in Appendix A.5). *Source.* Authors' computations using 2017 BdF.

[1]Rural: below 2,000 inhabitants, Small cities: between 2,000 and 20,000, Medium cities: 20,000 and 50,000, Large cities: over 50,000, Paris: Parisian agglomeration. In Appendix A.1, we provide a map of France corresponding to these categories.

To explain these differences in energy shares, we break down household energy use into two categories: *energy for housing* and *fuels for transports*, as shown in Table 2 in Appendix.[2]

Energy for housing accounts for 5.2% of total expenditures on average (56% of energy consumption), mostly for heating, hot water, cooling and cooking. It varies significantly across households, ranging from 6.3% in rural areas to 3.6% in Paris, and from 6% in Q1 to 4.1% in Q5. The primary determinant is the share of households living in a house, which is very high in rural areas (94%) and very low in Paris (22%), while it is more stable across income quintiles (44% to 64%). Additional data taken from 2017 *Fideli*[3] reveal that rural households have nearly twice the living space of Parisian households — an average of 105.6 square meters compared to 64 in Paris. Examining the disposable income distribution, we find that the wealthiest households (Q5) have an average living space of 108.6 square meters, while the poorest households (Q1) live in an average of 72.5 square meters.

Transport fuels account for 4.1% of total expenditures on average (44% of energy consumption), but regional differences are again more pronounced: 5.8% for rural areas versus 2.1% for Paris, compared to 4% for Q1 and 3.4% for Q5. Rural households almost universally own a car (93%) and use it for commuting (48%), whereas Parisian households rely more on public transportation and own cars less often. The number of vehicles and the necessity of commuting increase with income, resulting in relatively uniform transportation costs across income quintiles.

Overall, geography appears to be an important factor in explaining household energy shares, largely reflecting higher housing and transportation needs in rural areas. This pattern is observed in many countries (see Table 6 in Appendix A.2). According to the 2020 *Eurostat Household Budget Surveys*, in Germany, Spain, the Netherlands, and the United Kingdom, the share of energy in total household expenditure varies substantially between rural and urban areas, while remaining relatively stable across income quintiles. In the United States, data from the 2023 *Consumer Expenditure Survey* show a similar geographic gradient (8.3% in rural areas versus 5.7% in cities with more than one million inhabitants), although income differences are more pronounced than in Europe. Accounting for this geographic dimension is therefore crucial when assessing the distributive effects of carbon taxation, since fossil fuels represent the bulk of households' direct emissions. However, carbon taxes affect not only households but also the firms that employ them.

[2]Note that in the BdF survey, as in the US Consumer Expenditure Survey, it is not possible to distinguish between electricity expenditures for housing purposes and those for charging car batteries. We categorize all electricity expenditures in the category *energy for housing*.

[3]*Fideli* is a comprehensive administrative dataset built from French tax records that provides detailed information on dwellings and households. See details in Appendix A.3.

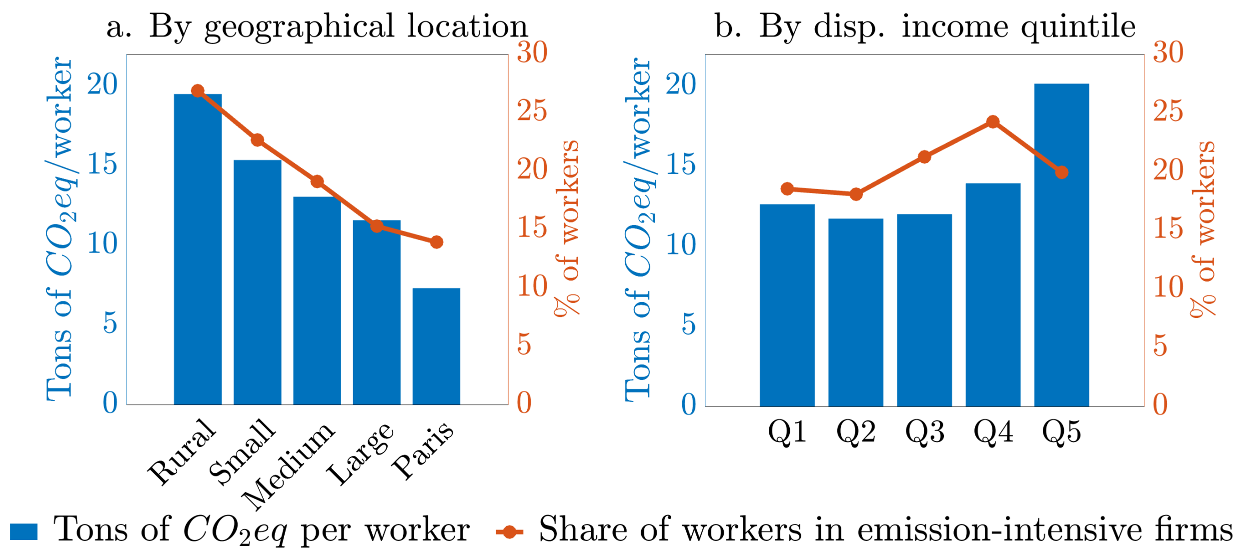
1.2 Firms' direct emissions

Some sectors, such as metalworking, agriculture, and transportation, have higher emissions and are therefore more affected by carbon taxes. These sectors are also unevenly distributed across regions and occupations, implying that both income and geography play a role in determining the firms where households are employed. This, in turn, shapes the distribution of the indirect costs of carbon taxes.

Data. We use administrative matched employer-employee data from France known as *BTS-Salariés* (BTS). The BTS dataset is exhaustive, containing 32 million workers per wave, providing rich demographic, geographic, and plant-level information. The large sample size enables us to conduct a detailed analysis by city code and to finely disaggregate employer and worker groups, which allows us to control for composition effects. Our contribution is to merge this dataset with sectoral emissions data from the 2022 National Accounts. To assess workers' exposure to a carbon tax on firms, we compute GHGs emissions per worker in each establishment of the economy. Using sectoral-level emissions and establishments' labor share, we construct plant-level emissions. We then build worker-level emissions by dividing plant-level emissions by employment. We favor establishment-level estimates since the biggest firms may own several establishments operating in distinct sectors. As a robustness check, we do the same exercise using firm-level data in Appendix A.4 and find very similar results.

Empirical results. We regress worker-level emissions, measured as "tons of CO_2eq per worker", on city type and income quintile, as described in Appendix A.5. The predicted tons of CO_2 per worker by city type and income are displayed in Figure 2. We also present its spatial distribution in Figure 3. Additionally, we present an extensive margin indicator showing the share of workers in emissions-intensive sectors. Emissions-intensive sectors are defined as those with emissions intensity above 5 tons of CO_2 per worker. Figure 2 reveals that rural households work in establishments that emit three times more than those employing Parisian workers (19.5 tons of CO_2 per worker versus 7.3). Moreover, considering that rural areas account for 24% of the population, compared to 19% for Paris, we find that establishments employing rural residents account for 36% of total firm emissions, versus 9% for Paris. Along the income dimension, wealthier households tend to work slightly more in emissions-intensive establishments and firms, but the gradient is steeper for the geography dimension.

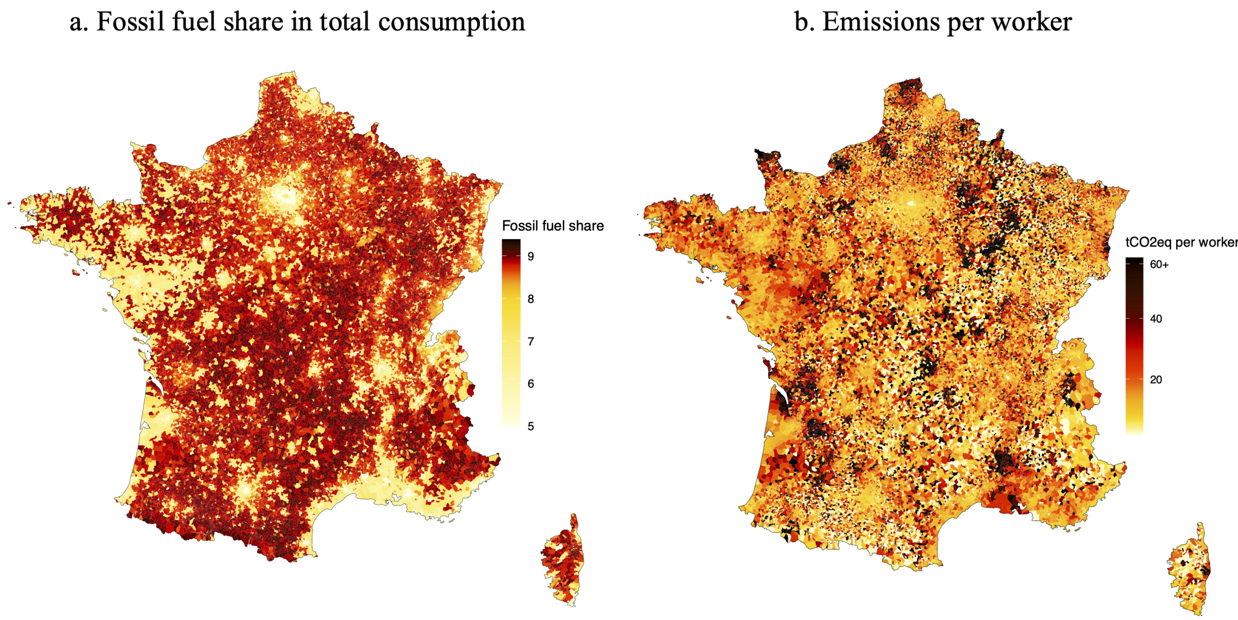
Figure 2: Emissions imputed to workers and % of workers in emissions-intensive firms



Notes. tons of $C0_2$eq imputed per worker, controlling for variables detailed in Appendix A.5. It represents the average tCO_2eq/worker in each group if the group had the same characteristics as the whole population. *Source.* Authors' computations using 2022 BTS and 2022 National Accounts.

We provide a sectoral decomposition along the income and geography dimensions in Table 8 in Appendix to explain these results. Workers in the two most polluting sectors, agriculture and industry, are heavily concentrated in rural areas: respectively 3% and 14.2% of rural households are employed in these sectors, against only 0.1% and 4.3% of Parisian households. In contrast, 0.4% and 15% of high-income households (Q5) work in agriculture and industry, compared to 2.5% and 5.6% of households in the lowest income quintile (Q1). In Table 9 in Appendix, we additionally show that rural households represent 46% of all agriculture workers and 30% of manufacturing workers, compared to 0.4% and 3% for Parisian households. Therefore, because both rural and wealthier households are more likely to be employed in emissions-intensive sectors, they may be more affected by the introduction of a carbon tax on energy consumed by firms.

Figure 3: Spatial distribution of fossil fuel share and emissions per workers



Notes. Fossil fuel shares and emissions per worker estimated at the city code level, see Appendix A.6.
Sources. *a*: 2017 BdF and 2021 households fiscal declarations. *b*: 2022 BTS and 2022 national accounts.

In conclusion, geography plays a significant role in explaining both households' fossil fuel share and firms' emissions intensity. As a result, households in rural areas will be affected by the introduction of a carbon tax in two ways: first, through their higher fossil fuel consumption, and second, because they work for firms that are more emissions-intensive. The role of income is less straightforward: while energy consumption is a necessary good, wealthier households tend to work in more polluting sectors. Therefore, to fully understand the distributive effects of carbon taxes, we need to develop a model that incorporates these geographic and sectoral differences.

2 A spatial heterogeneous-agent model

We combine a heterogeneous-agent framework à la Aiyagari (1994), in which idiosyncratic productivity shocks generate income and wealth heterogeneity, with a spatial structure featuring segmented labor and housing markets, region-specific subsistence energy needs, and endogenous migration decisions. Households choose their location subject to migration frictions: they face a monetary migration cost and, if they move, must sell their home. They consume energy (either clean or fossil), a composite consumption good, and choose whether to rent or own housing. The production side consists of a regional final-good producer in each area, combining capital, labor, electricity, and imported fossil fuels as inputs. In addition, a national representative firm generates electricity using capital and imported fuel. A rental firm intermediates the housing market by buying and selling houses to households and collecting rental income. Finally, the fiscal authority has access to a full set of policy instruments and levies carbon taxes either on households (τ^h) or on firms (τ^f). Carbon tax revenues are used either to increase public spending or to finance targeted transfers. Our algorithms, developed from scratch in MATLAB, are described in detail in Appendix B.

2.1 Households

The economy is populated by a continuum of households indexed by i, who are heterogeneous in two dimensions. The "vertical" heterogeneity is related to the idiosyncratic productivity process z, creating a distribution for wealth and income. The "horizontal" heterogeneity is related to the living area, with several household types k ranking households from "rural" to "urban", depending on the size of the city they live in. The living area determines the minimum subsistence energy consumption level $\bar{e}(k)$, the energy mix parameter $\gamma_h(k)$, housing price $p^H(k)$, rental price $\rho^H(k)$, wage $w(k)$, and the productivity process, so that the individual productivity is denoted $z(k)$. Households optimally choose their location, taking into account a fixed migration cost: $\kappa^{\text{mig}}(k, k') \geq 0$. Additionally, households differ by their housing status, as they choose whether to rent or own (in which case they pay the house price, depreciation, property taxes, and selling costs) their dwelling. As in Ferriere and Navarro (2025), we assume a preference shock that follows a Gumbel distribution with variance ϱ.

Households maximize intertemporal utility, choosing consumption c, labor supply l, housing status $h \in \{r, o\}$ (renting or owning), location k, asset a, energy bundle e^h (composed of electricity N^h and fossil fuel F^h with the carbon tax τ^h), subject to their budget constraint, their idiosyncratic productivity process and a borrowing constraint. Denoting respectively a, z, k, h the assets, productivity, location and housing status at the beginning of the period, and x' the next period of variable x, households maximize their value function

$$V(a, z, k, h) = \max_{\{U, a', k', h'\}} \{U + \beta \mathbb{E}\left[V(a', z', k', h')|k, z\right]\}$$

such that equations 1 to 7 below hold:

$$U = \frac{\left[(1-\chi)\mathcal{C}^{1-\nu} + \chi \mathcal{H}^{1-\nu}\right]^{\frac{1-\theta}{1-\nu}} - 1}{1-\theta} - \phi \frac{l^{1+\psi}}{1+\psi} \tag{1}$$

Equation 1 is the utility function. The first part is a function of a composite good $\mathcal{C}$ (defined in 2) and housing services $\mathcal{H}$ (defined in 4), as in Kaplan, Mitman and Violante (2020). χ measures the relative taste for housing services, $1/\nu$ measures the elasticity of substitution between housing services and consumption, and $1/\theta$ measures the intertemporal elasticity of substitution. The second part is the labor disutility, with ϕ scaling the disutility and $1/\psi$ the Frisch elasticity.

$$\left(\frac{c}{\mathcal{C}}\right)^{\frac{\sigma-1}{\sigma}} + \Lambda\left(\frac{e^h - \bar{e}(k)}{\mathcal{C}^{\epsilon}}\right)^{\frac{\sigma-1}{\sigma}} = 1 \tag{2}$$

Equation 2 implicitly defines the consumption bundle $\mathcal{C}$ following Comin, Lashkari and Mestieri (2021), which is appealing for two reasons. First, it introduces a non-homotheticity for the energy consumption that does not vanish with income: energy represents a higher share of total consumption expenditure for poor households, and stays a non-homothetic good even for high income. Second, this utility function allows for imperfect substitution between energy and other goods, with a constant elasticity of substitution σ. Here, Λ controls the share of expenditures devoted to energy e^h, and ϵ controls the income elasticity of energy demand. We also introduce a minimum subsistence level in energy $\bar{e}(k)$ that differs across living areas, accounting for higher energy needs in rural areas compared to urban areas (lack of public transportation, less efficient transportation system, bigger houses...).

$$e^h = \left[(1-\gamma_h(k))^{\frac{1}{\epsilon_h}}\left(N^h\right)^{\frac{\epsilon_h-1}{\epsilon_h}} + \gamma_h(k)^{\frac{1}{\epsilon_h}}\left(F^h\right)^{\frac{\epsilon_h-1}{\epsilon_h}}\right]^{\frac{\epsilon_h}{\epsilon_h-1}} \tag{3}$$

Equation 3 describes the energy bundle of the household. The elasticity of substitution between fossil fuel and electricity is determined by the parameter ϵ_h, and the energy mix depends on the living area with the parameter $\gamma_h(k)$.

$$\mathcal{H} = s^r(k)\mathbb{I}_{h=r} + \omega s^o(k)\mathbb{I}_{h=o} \tag{4}$$

Equation 4 describes housing services for households. Renting households ($h = r$) enjoy a housing size s^r, while homeowners ($h = o$) enjoy a housing size s^o multiplied by $\omega > 1$, capturing the possibility of additional utility from homeownership. House sizes vary by location and by tenure status, reflecting the empirical facts that houses are larger in rural areas and for homeowners.

$$\begin{aligned}&\underbrace{(1+\tau^{\text{VAT}})\left[c + p^N N^h + (p^F + \tau^h)F^h\right]}_{\text{Total consumption expenditures}} + \underbrace{\mathrm{H}(h, h', k)}_{\text{Housing expenditures}} + \underbrace{a' - a}_{\text{Savings}} + \underbrace{\kappa^{\text{mig}}(k, k')}_{\text{Migration cost}} \\ &= \underbrace{\Gamma\left(z(k)w(k)l\right)}_{\text{Net labor income}} + \underbrace{\left(1-\tau^k\right)\left(ra + \Pi(z)\right)}_{\text{Net capital income and profits}} + \underbrace{T(k, z, a)}_{\text{Transfers}}\end{aligned} \tag{5}$$

Equation 5 defines the budget constraint of households, subject to four taxes. Good and energy consumptions are subject to a VAT tax at a rate τ^{VAT}. Fossil fuel with relative price p^F is subject to an excise carbon tax τ^h. On the revenue side, labor income is taxed according to a progressive tax rule $\Gamma(\cdot)$ defined later. Capital income and profits are subject to a flat tax at rate τ^k. Finally, households receive lump-sum transfers from the fiscal authority, which may depend on their disposable income level or place of residence. On the expenditure side, revenues can be used for consumption, savings, housing, or migration costs.

$$\begin{aligned}\mathrm{H}(h, h', k, k') = & \underbrace{\rho^H(k')s^r(k')\mathbb{I}_{h'=r}}_{\text{Renting}} + \underbrace{(\delta^h + \tau^{\text{prop}})p^H(k)s^o(k)\mathbb{I}_{h=o}}_{\text{Owning}} \\ & + \underbrace{p^H(k')s^o(k')\mathbb{I}_{h=r,h'=o}}_{\text{Buying}} - \underbrace{(1-\kappa^{\text{sell}})p^H(k)s^o(k)\mathbb{I}_{h=o,h'=r}}_{\text{Selling}} \end{aligned} \tag{6}$$

Equation 6 describes housing expenditures. Rents, house prices, and housing sizes are location-specific. Renting households pay rent ρ^H for housing size s^r. Homeowners incur a depreciation cost δ^h and pay a property tax τ^{prop} proportional to the house price p^H and housing size s^o. Households that purchase a house pay the house price, while households that sell receive the house price net of a transaction cost κ^{sell}. Additionally, we assume that homeowners who wish to migrate must sell their house and rent in their next location, which creates an additional mobility friction for homeowners.

$$a \geq \underline{a} \tag{7}$$

Equation 7 depicts the borrowing constraint leading to imperfect capital markets. Households cannot borrow more than $-\underline{a}$, so that some agents will be constrained and "hand-to-mouths", creating households with high marginal propensity to consume at the bottom of the wealth distribution.

2.2 Production: goods, energy and housing

2.2.1 Regional Goods & Services sector

The consumption good (Y) is produced competitively in each living area k using labor L^Y, capital K^Y and energy bundle e^Y (composed of electricity N^Y and fossil fuel F^Y with the carbon tax τ^f). We assume that goods in each region are perfect substitutes, so that $Y = \sum_k Y_k$. Good producer in region k solves the following program:

$$\max_{\{L_k^Y, K_k^Y, e_k^Y, F_k^Y, N_k^Y, Y_k\}} \Pi_k^Y = Y_k - r^K K_k^Y - w(k)L_k^Y - (p^F + \tau^f)F_k^Y - p^N N_k^Y$$

such that

$$Y_k = \left[(1-\omega_y(k))^{\frac{1}{\sigma_y}} \left((K_k^Y)^{\alpha} (L_k^Y)^{1-\alpha} \right)^{\frac{\sigma_y - 1}{\sigma_y}} + \omega_y(k)^{\frac{1}{\sigma_y}} (e_k^Y)^{\frac{\sigma_y - 1}{\sigma_y}} \right]^{\frac{\sigma_y}{\sigma_y - 1}}$$

$$e_k^Y = \left[(1-\gamma_y)^{\frac{1}{\epsilon_y}} (N_k^Y)^{\frac{\epsilon_y - 1}{\epsilon_y}} + \gamma_y^{\frac{1}{\epsilon_y}} (F_k^Y)^{\frac{\epsilon_y - 1}{\epsilon_y}} \right]^{\frac{\epsilon_y}{\epsilon_y - 1}}$$

$\omega_y(k)$ is region-specific, reflecting the fact that carbon-intensive sectors are often located in rural areas, whereas less carbon-intensive service firms are more common in urban areas. All other parameters $(\delta, \alpha, \sigma_y, \gamma_y, \epsilon_y)$ are similar across regions. Since labor supply is not uniformly distributed and production function parameters differ across regions, wages $w(k)$ are region-specific. Hassler, Krusell and Olovsson (2021) points toward a very low short-run substitutability between energy and other inputs once the technology factors have been chosen. Moreover, Casey (2024) shows that Cobb-Douglas production functions with energy inputs vastly overestimate transitional emissions adjustments. Both papers motivate our choice for a CES production function, with σ_y being the elasticity of substitution between energy and non-energy inputs. Moreover, we assume constant return to scale since Lafrogne-Joussier, Martin and Mejean (2026) finds a full pass-through of positive energy price shocks using French firm microdata. Finally, the energy used by the firm is a bundle of electricity and fossil fuel, with an elasticity of subtitution governed by the parameter ϵ_y.

2.2.2 National electricity sector

Electricity N (for Nuclear) in our model is a consumption good for households (N^h) and an intermediary input for firms (N^Y). We assume electricity is produced competitively: the firm chooses capital K^N and fossil fuel F^N to maximize the profit $\Pi^N = p^N N - r^K K^N - (p^F + \tau^f) F^N$, subject to the production function $N = (K^N)^{\zeta} (F^N)^{1-\zeta}$.

2.2.3 Imported fossil fuel sector and the rest of the world

Fossil fuel is imported from the rest of the world, at a price p^F that reacts to the demand: $p^F = \bar{p} F^{\delta_F}$. The rest of the world uses this revenue to import goods X from the domestic economic. The budget constraint of the rest of the world – or equivalently the equilibrium condition for the current account of both the domestic economy and the rest of the world – is then $X = p^F F$. This assumption is a reduced-form representation of the rest of the world, while still allowing fossil fuel prices to adjust following a decline in domestic demand.

2.2.4 Regional rental sector and housing supply

We follow Kaplan, Mitman and Violante (2020), and assume that in each region k, a competitive rental sector owns H_k housing units at the beginning of the day, and chooses the future stock H'_k to be rented, subject to a location-specific operating cost $\eta(k)$ for each unit of housing rented out. Thus the renting activity generates $(\rho^H(k) - \eta(k))H'_k$. The rental sector also buys new houses to rent and pays $p^H(k)H'_k$, and sells old houses subject to a maintenance and tax cost, so it earns $p^H(k)(1-\delta^h-\tau^{\text{prop}})H_k$. Therefore, the profit of the rental sector is: $\Pi^r_k = [\rho^H(k) - \eta(k)]H'_k - p^H(k)[H'_k - (1-\delta^h-\tau^{\text{prop}})H_k]$. The rental company discounts future profits at the interest rate, so that it solves the problem: $J(H_k) = \max_{H'_k}\{\Pi^r_k\} + \frac{1}{1+r}\mathbb{E}\left[J(H'_k)\right]$. We obtain the condition linking the renting price $\rho(k)$ to the buying price $p^H(k)$:

$$\rho^H(k) = \eta(k) + p^H(k) - \frac{1-\delta^h-\tau^{\text{prop}}}{1+r}\mathbb{E}[(p^H)'(k)]$$

2.3 Fiscal authority

The fiscal authority gets revenue from taxes on labor income, capital income, housing property, consumption and fossil fuels. It is used to fund transfers (T), public spending (G) and public debt repayment ($r\bar{d}$). Denoting $\mu(a,z,k,h)$ the measure of households with state (a,z,k,h), the aggregation over all households is given by $X = \int x \, \mathrm{d}\mu(a,z,k,h)$ for $x \in \{a, c, F^h, N^h\}$. The regional aggregation is $F^Y = \sum_k F^Y_k$, $H = \sum_k H^S_k$ and $\Pi = \sum_k \Pi^r_k$. The government has the following budget constraint:

$$\begin{aligned} T + G + r\bar{d} = \int [zwl - \Gamma(zwl)]\,\mathrm{d}\mu + \tau^k(rA+\Pi) + \tau^{\text{VAT}}\left(C + p^N N^h + p^F F^h\right) \\ + \tau^{\text{prop}} H + \underbrace{\tau^h(1+\tau^{\text{VAT}})F^h + \tau^f(F^Y + F^N)}_{\text{Carbon tax revenue (CTR)}} \end{aligned}$$

Following Heathcote, Storesletten and Violante (2017), we assume a progressive labor tax $\Gamma(zwl) = \lambda(zwl)^{1-\tau}$. We choose to include the interaction term between VAT tax τ^{VAT} and the carbon tax on households τ^h in the carbon tax revenue so that there is no carbon tax term in consumption tax revenue. Apart for the carbon tax revenue, the budget constraint clears with G. However, the carbon tax revenue can be separately allocated either to finance an increase in public spending, or to fund lump-sum transfers towards households, possibly contingent on income and location. We explore these different scenarios in section 5.

2.4 Market clearing conditions and equilibrium

We denote $\mu^{\bar{k}} = \mu(a, z, k = \bar{k}, h)$ the regional aggregation of households of type $\bar{k}$. The firm aggregation is $X = \sum_k X(k)$ for $X \in \{K^Y, Y, I^Y, F^Y, N^Y\}$. To close the model, we have the following market clearing conditions:

$$\begin{cases} A = K^Y + K^N + \bar{d} & \text{(Asset)} \\ \forall k, \int z(k)l(k)\ \mathrm{d}\mu^k = L^Y_k & \text{(Labor)} \\ \forall k, \int h(k)\ \mathrm{d}\mu^k = H^{\mathrm{S}}(k) & \text{(Housing)} \\ Y_t = C + I + G + X + \mathcal{K}^{\mathrm{mig}} + \mathcal{K}^{\mathrm{sell}} + \mathcal{O} & \text{(Goods and services)} \\ F = F^N + F^Y + F^h & \text{(Fossil fuel)} \\ N = N^Y + N^h & \text{(Electricity)} \end{cases}$$

The goods and services production (Y) is consumed by households (C), government (G) or foreigners (X), or invested by firms and homeowners (I),[4] or paid in migration cost $\mathcal{K}^{\mathrm{mig}} = \int \mathcal{K}^{\mathrm{mig}}(k, k')\mathrm{d}\mu$, in selling cost $\kappa^{\mathrm{sell}} = \int \kappa^{\mathrm{sell}} \mathbb{I}_{h=o,h'=r}\mathrm{d}\mu$, or in operating cost $\mathcal{O} = \sum_k \eta(k)$.

We define the equilibrium as paths for households decisions, firms decisions, relative prices, fiscal policies and public expenditures[5] such that, for every period t, (i) households and firms maximize their objective functions taking as given equilibrium prices and taxes, (ii) the government budget constraint holds, and (iii) all markets clear.

3 Calibration on French macro and micro data

As this paper studies the distributive effects of carbon taxation, the calibration aims primarily to match the energy mix used by households and firms in France across locations and income groups. As documented in Section 1, households in rural areas consume more energy and fossil fuels than those in large cities and tend to work in more emission-intensive firms. We estimate idiosyncratic risk in each region and migration patterns using administrative matched employer-employee data. As detailed in Appendix B, our strategy is to directly incorporate parameters as guesses in the model so that each aggregate target is exactly matched. This section explains the targets associated with each parameter. Parameter values are reported in Table 11 in Appendix C, and untargeted moments are shown in Appendix C.4.

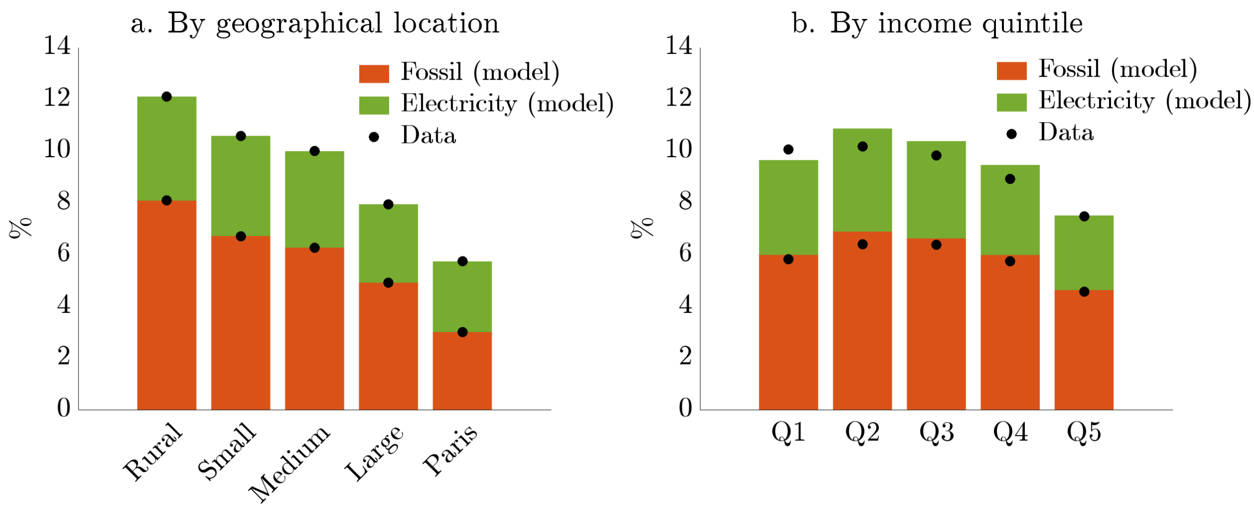
[4] $I = I^Y + I^N + I^H$, with $I^Y = (K^Y)' - (1-\delta)K^Y$, $I^N = (K^N)' - (1-\delta)K^N$ and $I^H = H' - (1-\delta^h)H$.

[5] Households: $\{C_t, H_t, N^h_t, F^h_t, A_{t+1}\}_t$, firms: $\{Y_{k,t}, L^Y_{k,t}, K^Y_{k,t}, F^Y_{k,t}, N^Y_{k,t}, N_t, K^N_t, F^N_t\}_{k,t}$, relative prices: $\{r_t, w(k)_t, p^F_t, p^N_t, p^H(k)_t, \rho^H(k)_t\}_{k,t}$, fiscal policies: $\{\Gamma(.), \tau^k, \tau^{\mathrm{VAT}}, \tau^h_t, \tau^f_t\}_t$ and public expenditures: $\{T_t, G_t\}_t$.

3.1 Households

Consumption. We use Λ to match the average energy share in total expenditures, and ϵ to fit the energy share of households within the Q5 of disposable income. We set the $\bar{e}(k)$ to match the average energy share in each city type (normalizing $\bar{e}(\text{Paris})$ to 0), and $\gamma(k)$ to have the right energy mix in each area, as shown in Figure 4.a.

Figure 4: Energy share in total consumption

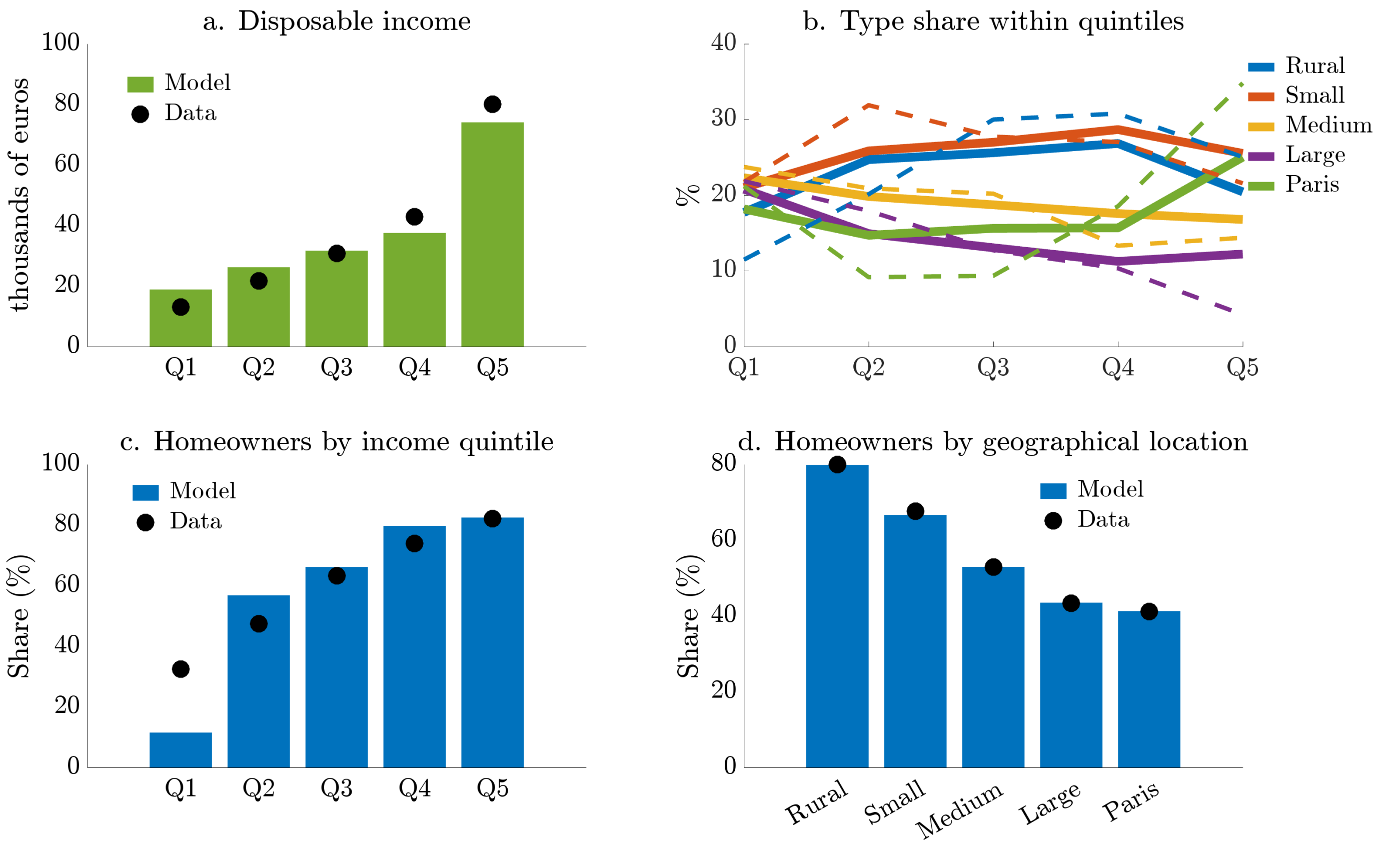


Notes. b: fossil fuel and electricity shares by disposable income quintile are untargeted except for Q5. *Source.* Authors' computations using 2017 BdF.

We estimate the elasticity of substitution between energy and G&S consumption to $\sigma = 0.2$, using National Accounts longitudinal data from 1959 to 2021 (the data and method are described in Appendix C). We set the elasticity of substitution between fossil fuel and electricity to $\epsilon_h = 1.5$. Literature estimates range from 0.02 in the short-run in Hassler, Krusell and Olovsson (2021) to 2 in the long-run for Papageorgiou, Saam and Schulte (2017): we choose this value to be the same as the one selected for firms (ϵ_y), estimated in Fried, Novan and Peterman (2024). In Appendix C.2, we provide robustness check for alternative values of σ, ϵ_h and ϵ_y.

Income process. As in Labrousse and Perdereau (2025), we directly estimate the Markov process for idiosyncratic productivity z using data on hourly wages between 2015 and 2019 from the *Panel tous salariés*. Compared to this paper, we estimate one Markov matrix for each of our five city types, keeping only workers that do not migrate between city types. Therefore, we do not directly target the income distribution or the correlation between income and location and present these untargeted moments in Figure 5. We are close to the observed disposable income distribution from the 2021 Insee report *"Revenus et patrimoine des ménages"* (RPM) (panel *a*). Our model recovers the main features of the correlation between income and locations from 2017 BdF (panel *b*). Parisian households are richer than average, as they account for 26% of the top income quintile but only 19% of the population. Households living in rural areas or small cities are more concentrated in the middle of the distribution, with over-representation in Q2, Q3 and Q4, and under-representation in Q1 and Q5.

Figure 5: Income distribution and homeownership



Notes. Moments in panels a, b, c are untargeted. b: share of each geographical location type within each quintile in data (solid lines) and in the model. *Sources.* a: 2021 HVP. b: 2017 BdF. c and d: 2017 Fideli.

Housing, rental firms, and housing supply. Data concerning homeownership rates and housing sizes are taken from an exhaustive administrative dataset (2017 *Fideli*, explanations in Appendix A.3). The additional utility from owning a house, ω, is calibrated to match the homeownership rate in France (59.5%). In rural, small, medium, large cities, and Paris, the average dwelling size in square meters is $s^r = [82, 71, 65, 61, 54]$ for renters and $s^o = [112, 106, 96, 89, 78]$ for homeowners. In the utility function, the parameter χ is set so that rents, including imputed rents, account for 16% of household expenditures, and $\nu = 0.8$ as in Kaplan, Mitman and Violante (2020).

The operating cost $\eta(k)$ in each region is calibrated to match the homeownership rate by region, as illustrated in panel d of Figure 5. We recover that the homeownership rate is twice as high in rural areas as in Paris and increases with income (untargeted). The housing supply scaling parameters $\{\Xi(k)\}_{k=1,2,3,4}$ are set to match the population share of each region in France: 23.5%, 26.0%, 18.5%, 13.4%, and 18.6% for Rural, Small, Medium, Large, and Paris, respectively. The last parameter, $\Xi(5)$, is set to match the ratio of housing wealth to GDP, $\frac{p^h H}{\text{GDP}} = 3$. The price elasticity of housing supply is set to $\delta_H = 0.2$, which lies within the range of commonly used values in the housing literature: 0.1 in Murphy (2018) and 0.3 in Baum-Snow and Han (2024). Profits from all rental firms are distributed back to households proportionally to their productivity level z such that $\Pi(z) = \frac{z}{\int z} \sum_k \Pi_k^r$.

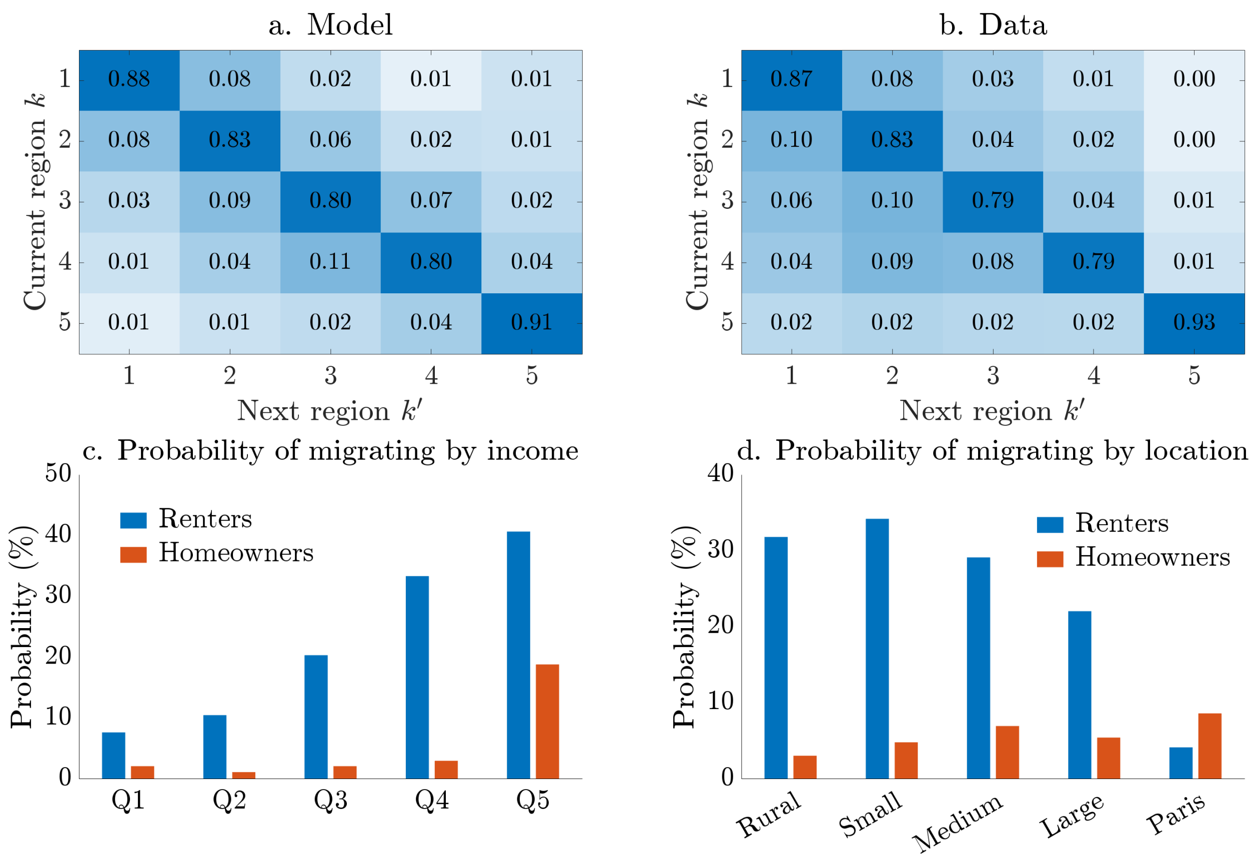
3.2 Migration frictions

Migration frictions are key to shaping the regional distributional effects of carbon taxation. If migration were frictionless, relocation would be immediate and the tax burden would be equalized across locations. In the model, we consider three types of migration frictions.

The first friction relates to *migration costs* for households that are able to move. We introduce monetary migration costs $\kappa^{\text{mig}}(k, k')$ to match the empirical probability of moving from region k to region k'. We first compute the empirical migration matrix over a 5-year horizon.[6] Specifically, we compute the probability of being in region k' at $t+5$ conditional on being in region k at t. We then construct a 5×5 matrix of migration costs κ to match this empirical matrix, normalizing the diagonal to zero to capture zero cost of staying in the same region. Panels *a* and *b* of Figure 5 compare migration probabilities in the data and in the model. The model fits the data well and replicates three key facts. First, about 85% of households remain in their region over five years, implying an annual migration probability of roughly 3% ($1 - 0.85^{1/5}$). Second, movers tend to relocate to similar regions (*i.e.*, probabilities concentrated near the diagonal), with very few moves between extremes such as Paris and rural areas. Third, very few people move to Paris, and 93% of Parisians remain there after five years (98.6% after one year). Appendix C.3 compares our implied migration costs with the two main approaches used in the literature: estimating monetary moving costs directly from data or structural models, and inferring migration elasticities from migration responses to tax changes.

[6] To construct this matrix, we use the 2016–2021 *Panel tous salariés*. We keep workers aged 30-55 with annual wages above €2,100 who are present in the dataset throughout 2016–2021, yielding a sample of more than 1 million workers.

Figure 6: Migrations by location, income and housing status



Notes. *a* and *b*: probability of migrating after 5 years from k towards k' with $\{1, 2, 3, 4, 5\} = \{$Rural, Small, Medium, Large, Paris$\}$. *c* and *d*: probability of migrating after 5 years in the model, by income quintile, location and housing status. *Source.* *b*: 2016-2021 *Panel tous salariés.*

The second friction relates to *housing status*. We assume that homeowners who migrate must sell their home and rent in the destination location, creating an additional mobility friction. Panels *c* and *d* of Figure 6 show that housing status strongly shapes five-year migration probabilities. In the model, the average five-year migration rate is 22.5% for renters, compared with 5.4% for homeowners. Migration also varies sharply with income: some low-income households may be effectively "trapped" and unable to pay the migration cost. The five-year migration probability is 4.2% for households in the first income quintile, versus 28.7% in the top quintile.

Finally, we introduce a third friction: a share of *immobile households* that cannot move, or equivalently face an infinite migration cost. We set this share to 15% of the population, evenly distributed across regions. These households capture individuals with strong location-specific attachments, such as older households, homeowners facing high transaction costs, or workers tied to local labor markets and social networks.

3.3 Firms

Goods and services firm. The energy share $\omega_y(k)$ is city-specific and accounts for the share of each regional firm in total emissions, as illustrated in Figure 2. Taking into account population shares: Rural, Small, Medium, Large, and Paris respectively accounts for 35.8%, 28.6%, 17.3%, 9% and 9% of firms' direct emissions. We follow Fried (2018) and set the elasticities of substitution between energy and the capital-labor bundle, and between electricity and fossil fuel, to respectively $\sigma_y = 0.05$ and $\epsilon_y = 1.5$. These elasticities lie within the range of estimates from Papageorgiou, Saam and Schulte (2017): we provide robustness check for alternative values in Appendix F. The capital share is set to $\alpha = 0.31$ to match the share of labor revenue $\frac{wl}{\text{GDP}} = 65\%$ following Cette, Koehl and Philippon (2019). The share of fossil fuel in the policy mix is set to $\gamma_y = 0.86$ such that electricity accounts for 33% of the regional firms' energy mix. Finally, the depreciation rate is set to $\delta = 11.8\%$ to match the aggregate share of investment as in Auray et al. (2022).

Electricity firm and other parameters. The electricity sector is capital intensive, so we set $\zeta = 0.9813$ to have $\frac{F_N}{F} = 1\%$. We assume that electricity is produced using few fossil fuel inputs because France relies mainly on nuclear power plants and hydroelectricity from dams. The initial price p^F of the imported fossil fuel is set such that fossil fuel imports account for 4% of the GDP. Finally, in our main quantitative exercise in Section 4, we suppose the price of fossil fuel is fixed and does not react to the domestic demand ($\delta^F = 0$): this small-open economy assumption will be relaxed in Section 6.

3.4 Fiscal authority

Following Labrousse and Perdereau (2025), transfers T are set at 9.6% of GDP (sickness and disability, family and children, social exclusion, and unemployment benefits), effective tax rate on consumption is $\tau^{\text{VAT}} = 12.9\%$, average labor tax is $\lambda = 0.671$, and labor tax progressivity is $\tau^l = 0.095$. Housing tax is set at $\tau^{\text{prop}} = 1\%$.[7] Public debt d is set at 100% of GDP as in 2017 and the effective capital income tax rate is set to $\tau^k = 9.02\%$ as computed in Auray et al. (2022). Initial carbon taxes, τ^h and τ^f, are calibrated to match effective tax rates of €183.5 per ton of CO_2 and €60.9 per ton of CO_2, respectively.[8] We close the budget constraint of the government by adjusting public spending and get $G = 23\%$ of GDP.

[7]We sum property tax, inheritance tax, transfer rights, and real estate wealth tax from aggregate fiscal data, and obtain 3% of GDP. As the housing-to-GDP ratio is 3, the housing tax is $\tau^{\text{prop}} = 1\%$.

[8]*Rapport sur l'impact environnemental du budget de l'État 2024, PLF 2025.* See more here.

4 Quantitative results

In this section, we increase carbon taxes τ^h or τ^f and compute the welfare change associated with the transition.

Experiment. The experiment proceeds as follows. We start from the initial steady state described in Section 3. At $t = 1$, we introduce an unexpected shock to the path of τ^h or τ^f. From $t = 1$ onward, the path is perfectly anticipated by agents. The shock is permanent, with the final tax level calibrated to reduce emissions by 10% in the new steady state. The tax increases linearly: it rises from τ^{init} to τ^{final} over 10 periods and remains at τ^{final} for $t \geq 10$. In this benchmark experiment, carbon tax revenues are used to increase public spending, which allows us to isolate the distributive effects of carbon taxation. We consider alternative rebate schemes and alternative valuations of public spending in Section 5.

Welfare measure. Welfare changes are measured in consumption-equivalent (CE) terms. As households consume several goods in the model, we express the consumption equivalent in terms of total expenditures Exp associated with the bundle $\mathcal{C}$, composed of the consumption good c and energy e^h. Specifically, we compute the change in steady-state consumption expenditures that makes a household indifferent between remaining at the status quo and going through the transition following the carbon tax increase. Formally, let $\Omega = (a, z, k, h)$ denote the household's initial state variables, and let $V_1^{\text{carbon tax}}(\Omega)$ be the value function for the same household in the first period of the transition. We then define the consumption-equivalent welfare change $\text{CE}(\Omega)$ such that:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left\{ U\Big((1 + \text{CE}(\Omega)) \text{Exp}(\mathcal{C}_t), \mathcal{H}_t \Big) - \phi \frac{l_t^{1+\psi}}{1+\psi} \right\} \mid \Omega \right] = V_1^{\text{carbon tax}}(\Omega)$$

Therefore, a consumption equivalent of $\text{CE} = -1\%$ means that a household would need to reduce its consumption expenditures in all periods by 1% to be indifferent between remaining at the steady state and going through the transition.

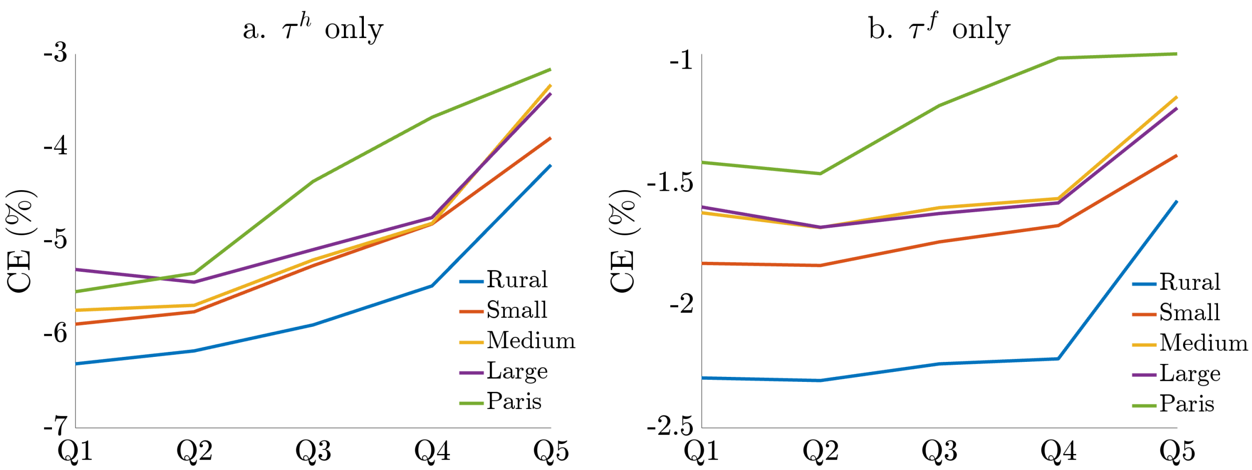
In the following paragraphs, we describe how τ^h and τ^f transmit to household welfare, by income quintile and location. We also examine the role of migration in shaping the distributive effects of carbon taxes, highlighting that the associated costs may differ between the short run and the long run.

4.1 The distributive effects of carbon taxes

The carbon tax burden varies significantly depending on location, income, and the type of tax. Figure 7 presents the average welfare effects (in consumption equivalent, as described above) by region and income quintile for the initial distribution, for an increase of τ^h only (left panel) and τ^f only (right panel). In Figure 14 and 15, we provide a decomposition of welfare by different channels for each location, quintile and housing status.

Before turning to the mechanisms, we highlight three main facts. First, reducing emissions by 10% entails a welfare cost: CE is negative because we assume that public spending G is not valued by households, in order to isolate the distributive effects of carbon taxation. The cost is larger under τ^h (-5.0% CE on average) than under τ^f (-1.7% CE). In consumption terms, households would be indifferent between the policy and remaining in the initial steady state with a permanent annual consumption loss of about €1,046 under τ^h, and €344 under τ^f. Second, both taxes are regressive, with larger welfare losses for poorer households, especially under τ^h. Third, welfare effects differ markedly across locations: Parisian households experience smaller losses on average, while rural households consistently face the largest ones. We now turn to the detailed distributional patterns.

Figure 7: Average welfare effect by region and income



Notes. Average welfare change between the first period of the transition and the initial steady state, expressed in consumption-equivalent terms.

Carbon tax on households (τ^h). Figure 14.*a–b* shows that the overall welfare impact of τ^h is driven mainly by two channels: the direct effect of the carbon tax and changes in housing rents ρ^H. The direct effect is strongest for households with high fossil fuel consumption, *i.e.* rural and low-income households, due to the non-homotheticity of energy consumption across income and regions. Specifically, welfare losses reach -5.7% CE in rural areas versus -4.1% in Paris, and -5.8% CE for Q1 versus -3.5% for Q5. The second main channel is changes in rental prices ρ^H. As rural households migrate to large cities, rents change by -4.2%, -1.5%, $+0.1\%$, $+5\%$, and $+7.5\%$ across the five regions, compared to initial steady state. This reduces welfare for households in large cities, where rents and renter shares are high, and for poor households who cannot buy a home. Figure 15.*a–b* shows that this effect primarily affects renters and tends to narrow the tax burden gap between rural and urban areas. Changes in buying prices, roughly similar to rents, have smaller welfare effects. Finally, second-order general equilibrium effects include higher rental firm profits due to rent increase, a slight increase in the interest rate benefiting capital owners, and a 4% wage decline in all regions, reducing welfare broadly. Overall, while the carbon tax disproportionately affects rural households due to energy use, migration and housing market adjustments partly mitigate the burden.

Carbon tax on firms (τ^f). Taxing fossil fuel consumption by firms alters their input mix and impacts households through changes in income and general equilibrium effects. As illustrated in Figure 14.*c* and *d*, the welfare impact of τ^f depends on adjustments in wages, housing rents, and the interest rate. Since firms in rural areas are more fossil fuel-intensive, the rise in fossil fuel prices reduces the demand for other inputs, particularly labor, leading to a decrease in wages of -4.8% in rural areas compared to -0.7% in Paris. This results in welfare costs of -2.2% CE and -1.1% CE, respectively. This decline in wages has smaller effects on poor people, for whom transfers represent a high share of revenue, and on rich households that rely more on capital income, creating and inverted U-shape for welfare loss by income quintile: households in Q1, Q2 and Q5 experiences a welfare loss of -1.8, -1.9 and -1.2% CE, respectively. Housing rents play a similar role that with τ^h. As rural households migrate to large cities to escape the wage decrease, rents move by respectively -3.5%, -1.6%, -0.1%, $+1\%$ and $+3.4\%$, in our five regions, compared to initial steady state. This creates a decrease in welfare for households in large cities, but a small gain for rural households. As illustrated in Figure 15.*c* and *d*, rural renters benefit from this change, while it accounts for almost half the welfare cost of Parisian renters. The similar change in buying price, conversely, benefits homeowners. Lastly, the reduction in firms' capital demand lowers the interest rate, which mostly affects wealthier households because capital income constitutes a larger portion of their earnings.

In conclusion, due to differences in households' energy consumption baskets for τ^h and firms' emissions intensity for τ^f, both carbon taxes disproportionately impact rural areas and lower-income households. Migration and housing price adjustments partially mitigate the welfare costs along the geographic dimension. For τ^h, the gradients associated to income and geography are similar; for τ^f, losses associated to location are stronger than those associated to income. These findings are important for the implementation of carbon tax policies or quotas: in Appendix D.3, we discuss how our results can be used to assess the welfare effects of the past and future EU-ETS quotas systems.

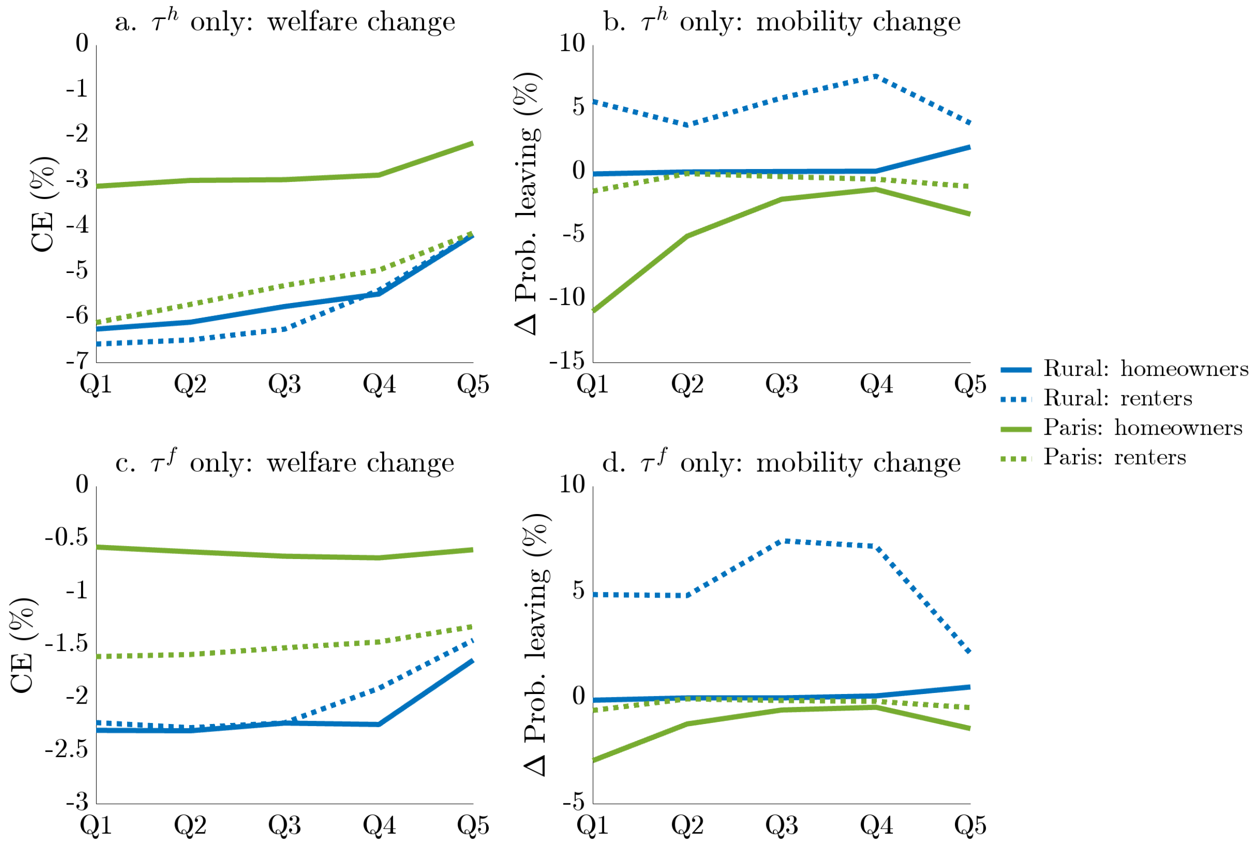
4.2 Migration and welfare

In this section, we examine how migration frictions shape the distributive effects of carbon taxes. As described in Section 3, mobility is limited by monetary migration costs, housing tenure, and a fraction of immobile households.

Migration and housing choices. Consistent with the data, renters are substantially more mobile than homeowners. As a result, rural renters can respond to higher carbon taxes by relocating to regions where welfare losses are smaller. Panels a and c of Figure 8 show that, under both τ^h and τ^f, regional differences in welfare costs are much smaller for renters than for homeowners. Migration allows rural renters to partially escape local adverse effects, such as higher direct energy costs under τ^h or lower wages under τ^f. The resulting increase in housing demand in large cities raises rents there and lowers rents in rural areas, contributing to the spatial equalization of welfare.

For homeowners, adjustment is more limited because moving requires selling property and paying transaction costs. As a result, homeowners, especially in rural areas, are less responsive to tax-induced regional shocks. Panels b and d of Figure 8 show that mobility increases mainly among rural renters (and only marginally among high-income rural homeowners), while mobility from Paris declines, reflecting the greater attractiveness of large cities after the reform. Rural homeowners therefore absorb a larger share of local wage or energy price shocks. In our calibration, homeowners account for about 80% of households in rural areas, implying that a large fraction of the rural population is effectively "trapped." In the model, being trapped reflects not only low income but also illiquid wealth tied to owner-occupied housing. While migration and rent adjustments partly equalize welfare across locations for mobile households, housing frictions prevent many rural homeowners from escaping the adverse effects of the carbon tax.

Figure 8: Welfare and change in mobility by income, location and housing status



Notes. *a* and *c*: welfare changes for τ^h and τ^f, for rural (blue) and Parisian households (green), separating homeowners (solid line) and renters (dotted line). *b* and *d*: changes in probability of leaving the area for τ^h and τ^f, for rural (blue lines) and Parisian households (green lines), separating homeowners (solid lines) and renters (dotted lines).

Migration and monetary costs. We repeat the exercise assuming a 50% increase in monetary migration costs and report the results in Figure 19 in Appendix. Average welfare losses remain very similar under both τ^h and τ^f, indicating that aggregate effects are largely unchanged. Mobility responses, however, differ markedly. Higher moving costs make relocation more difficult for low-income renters. For instance, the probability of leaving rural areas increases by only 2% for Q1 rural renters under both τ^h and τ^f, compared with about 5% in the benchmark. Mobility among renters now rises with income, reflecting tighter financial constraints for poorer households. As a result, even renters become partially "trapped" when moving costs are high. Consistent with the weaker mobility response, welfare gaps between renters across regions widen relative to the benchmark.

Counterfactual with no migration. To further isolate the role of migration, we shut it down entirely by assuming that all households are immobile across regions. The results are shown in Figure 20 in Appendix. Housing tenure remains a choice, but location is fixed.

Carbon tax paths are recalibrated to achieve the same 10% reduction in emissions. Without migration, average welfare losses are larger: -7.0% CE under τ^h and -2.1% CE under τ^f (instead of -5.0% and -1.7% in the benchmark). Geographical disparities now dominate income disparities: under τ^h, welfare losses are 2.5 times higher in rural areas compared to Paris (versus 1.4 in the benchmark), while across income quintiles they are 1.7 times higher for Q1 relative to Q5, as in the benchmark. Under τ^f, losses are 6 times higher in rural areas compared to Paris (versus 2 in the benchmark), while across income quintiles they are 1.3 times higher for Q1 relative to Q5 (versus 1.5). Housing tenure matters much less once migration is shut down: the welfare gap between renters and homeowners within a given region becomes small relative to the gap across regions.

Taking stock. Overall, these results highlight that migration is a key mechanism for smoothing regional disparities. By allowing households, especially renters, to relocate in response to changes in wages and housing costs, migration attenuates geographical inequalities and reduces the overall welfare cost of carbon taxation. In contrast, rural households, particularly homeowners with illiquid housing wealth, can become effectively trapped in high-loss locations, generating pronounced spatial inequalities.

5 Alternative transfer policies

The distributive effects of carbon taxation are crucial for its political acceptability. Our positive analysis in Section 4 showed that poor and rural households are more affected by carbon taxes, making them more likely to oppose them or protest, as illustrated by the Yellow Vest movement in France. In this section, we consider policies in which the government redistributes carbon tax revenues through targeted lump-sum transfers to modify the distribution of the tax burden. In practice, governments have several options to recycle these revenues, such as reducing existing taxes or investing in policies that mitigate incompressible energy consumption. However, we argue that transfers are particularly important for communication and political acceptability. By explicitly separating carbon tax revenues from the general state budget, transfers make it clear that the tax is intended to influence behavior rather than to finance public deficits.

We consider four scenarios, each targeting a 10% ex-post reduction in emissions between the initial and final steady states. In contrast to the previous section, where only τ^h or τ^f increased, we now assume that both taxes are scaled up by the same factor. The transfer rule in each scenario is as follows:

$$T(y_i, k_i) = \text{CTR} \cdot \begin{cases} 0 & \text{Scenario 1: Benchmark } G \\ 1 & \text{Scenario 2: Uniform} \\ \mu \cdot y_i^{-x} & \text{Scenario 3: Income} \\ \mu \cdot \left(y_i^{-x} + \gamma(k_i)\right) & \text{Scenario 4: Income} \times \text{Geography} \end{cases}$$

where T is the transfer rule, y_i the total household's income, k_i the location, CTR the carbon tax revenue, and μ the scaling parameter[9].

In the "**Benchmark *G***" scenario, carbon tax revenue is used to increase public spending G (which is not valued by households), and transfers are set to zero. In the "**Uniform**" scenario, all households receive the same transfer. In the "**Income**" scenario, the government chooses the progressivity parameter x that minimizes the distance between the welfare loss CE_i in scenario 1 and the rule $\mu \cdot y_i^{-x}$.[10] This scenario assumes that the government observes household income and can implement a progressive transfer (if $x > 0$), but cannot differentiate transfers by location k (or is legally restricted from doing so, as in France). Finally, in the "**Income × Geography**" scenario, we assume that 50% of carbon tax revenues (CTR) are redistributed based on income, as in scenario 3, and 50% based on geography.[11] Table 1 reports the average welfare for each scenario by location and income, as well as the standard deviation of the consumption equivalent, $\sigma(\text{CE})$. Figure 9 presents the 10th, 50th, and 90th percentiles of the welfare distribution within each location and income quintile. Finally, Figure 21 in Appendix presents the welfare decomposition for each scenario.

[9] The total income is $y = \Gamma(zwl) + (1 - \tau^k)(ra + \Pi) + \bar{T}$. The carbon tax revenue is $CTR = \tau^h(1 + \tau^{\text{VAT}})F^h + \tau^f(F^y + F^N)$. The scaling parameter μ is such that $\int_i T_i \mathrm{d}i = \text{CTR}$.

[10] Let CE_i denote the individual consumption equivalent in scenario 1. We compute $\min_{a,x} \int_i (\text{CE}_i - a y_i^{-x}) \, \mathrm{d}i$, which yields $x = 0.324$.

[11] Let $\text{CE}(k)$ denote the consumption equivalent by region in scenario 1. We set $\gamma(k) = \text{CE}(k) - \text{CE}(\text{Paris})$, scaled such that $\mu \int_i \gamma(k_i) \mathrm{d}i = 50\%$ of CTR.

Table 1: Welfare change by location and income

	Scenario	Rural	Small	Medium	Large	Paris	All	σ(CE)
(1)	Benchmark G	-3.13	-2.67	-2.54	-2.56	-2.00	-2.61	0.64
(2)	Uniform T	-0.96	-0.51	-0.32	-0.14	0.12	-0.41	0.42
(3)	Income T	-0.90	-0.44	-0.24	-0.06	0.14	-0.35	0.42
(4)	Income $\times$ Geography T	-0.48	-0.42	-0.33	-0.14	-0.32	-0.36	0.19
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**	**σ(CE)**
(1)	Benchmark G	-2.91	-2.97	-2.77	-2.55	-1.87	-2.61	0.64
(2)	Uniform T	-0.27	-0.46	-0.50	-0.53	-0.30	-0.41	0.42
(3)	Income T	-0.13	-0.37	-0.45	-0.51	-0.31	-0.35	0.42
(4)	Income $\times$ Geography T	-0.19	-0.32	-0.41	-0.49	-0.39	-0.36	0.19

Notes. Average welfare change between the first period of the transition and the initial steady state, expressed in consumption-equivalent terms.

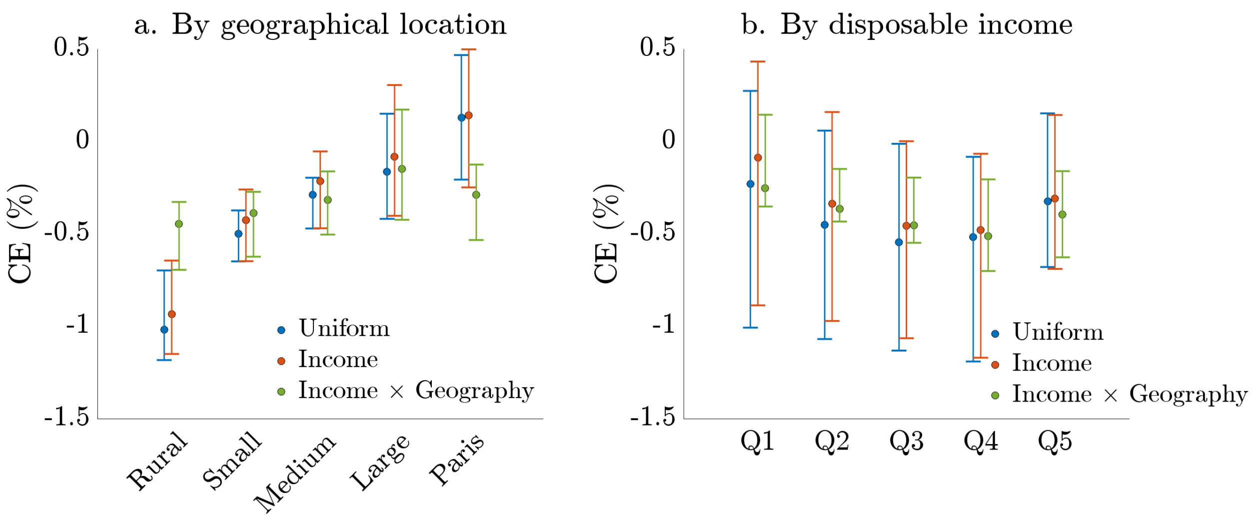
Our scenario G provides a benchmark for the distributive effects of carbon taxes when the use of carbon tax revenue is not taken into account. Because the revenue is used to increase G, which is not valued by households, and because emissions reductions do not directly benefit households, the welfare change is necessarily negative. We relax these assumptions in Section 6 by introducing a damage function and a valuation of public spending. Losses are 57% higher in rural areas than in Paris, and 56% higher for Q1 than for Q5. The aggregate welfare loss is -2.61% CE, corresponding to €546 per year.

In the "Uniform" scenario, carbon tax revenue is redistributed equally across households. Welfare increases relative to the benchmark because households can consume more, especially those with high marginal utility, and because transfers mitigate inefficiencies created by borrowing constraints by providing some insurance to low-income households. The uniform transfer strongly reduces inequality across income groups: welfare losses become roughly similar across income quintiles. However, it fails to compensate across locations. Rural households experience large losses relative to other regions, while Parisian households even benefit from the transition, as they receive transfers while paying little carbon tax. As illustrated in Figure 9, even the 90th percentile in rural areas lies below the 10th percentile in any other area, indicating that all rural households bear a disproportionate burden of the carbon tax. Moreover, within-quintile heterogeneity is large: the 10th percentile of the first quintile experiences losses of about -1% CE, while the 90th percentile enjoys a gain of 0.3% CE.

The "Income" scenario redistributes carbon tax revenue more toward poorer households. This slightly improves aggregate welfare, as these households have a higher marginal utility of consumption. As expected, gains are concentrated among low-income households receiving larger transfers. Figure 9 shows that this scenario slightly shifts the welfare profile upward across locations and income groups: the share of households experiencing a positive welfare change rises to 18.3%, compared with 15.7% under the uniform scenario. However, it does not reduce geographical or within-quintile dispersion. Geographical inequality remains, as poor Parisian households receive large transfers while richer rural households do not.

We therefore introduce the "Income × Geography" scenario, in which transfers vary by both location and income. Compared with the "Income" scenario, welfare losses are roughly halved in rural areas, while Parisian households now also experience losses. This scenario therefore equalizes the burden of the carbon tax along both geographical and income dimensions. The standard deviation of welfare losses is about half as large, which may appeal to a social planner concerned with minimizing maximum losses, promoting a fair transition, or avoiding a concentration of losers in rural areas, an important factor for the political acceptability of carbon taxation. Figure 9 illustrates this reduction in dispersion: within-quintile inequality declines substantially, and losses at the 10th percentile are much smaller than in previous scenarios (-0.7% instead of -1.2% in rural areas, and -0.4% instead of -0.9% in Q1). The only group that clearly loses from this transfer rule is Parisian households, who now experience losses similar to those in other areas. Note, however, that although this scenario produces more losers than the previous one, their losses are much smaller. As a result, once environmental damages are valued, as discussed in the next section, it will generate more winners.

Figure 9: Distribution of welfare within each location and income quintile



Notes. This represents the 10th, 50th and 90th percentiles of the welfare distribution (in CE) over the transition, for different transfer policies.

Therefore, we show that in the absence of location-specific rebates, rural households disproportionately bear the costs of the green transition. Implementing transfers that depend on both income and location equalizes welfare losses across space and along the income distribution, thereby increasing the political acceptability of carbon taxes.

6 Robustness and discussion

In this section, we discuss the sensitivity of our results to changes in key parameters. Moreover, in the main experiments above, we do not consider that households value public spending or that emissions create damage, which make the carbon tax detrimental for welfare. We relax these two assumptions below to see if the decrease in emissions and the increase in public spending following carbon taxes can compensate the welfare cost of the taxes. For each robustness check, we reproduce the "Benchmark G" scenario described before, where both taxes increase to reduce emissions by 10%, and the revenue increases public spending G.

Robustness. We calibrate the model using relatively low elasticities of substitution, reflecting households' and firms' limited short-run ability to adjust. We re-run the main experiments using alternative values for key elasticities (σ, σ_y, ϵ_y, ϵ_h, δ_H, δ_F), and report the results in Appendix F. Lower values of ϵ_y, σ, σ_y, and ϵ_h reduce the scope for substitution away from fossil fuels and energy, thereby widening the rural–Paris gap. Increasing the elasticity of housing supply (δ_H) also raises spatial inequality, as it limits the decline in housing prices in rural areas.

Damage function. Reducing emissions may reduce temperature increase and therefore yield global benefits. We suppose climate damages enter utility as: $\mathcal{D} = -\sum_{t=0}^{\infty}(\beta_{\mathcal{D}})^t \alpha_{\mathcal{D}}\, T_t^{1+\Sigma_{\mathcal{D}}}$, where T denotes global temperature that responds to cumulative emissions, as detailed in Appendix F. Damages are discounted at $\beta_{\mathcal{D}} = 0.98$ and we calibrate $\alpha_{\mathcal{D}} = 0.039$ and $\Sigma_{\mathcal{D}} = 0.666$ such that welfare losses are -15% (resp. -35%) CE under a $+1.5$°C (resp. $+3$°C) warming by 2100, as in Bilal and Känzig (2026). Given France's limited contribution to global emissions,[12] we assume that global emissions decline at the same rate as French emissions. The resulting reduction lowers global mean temperature by 0.13 °C in 2100.[13] The average welfare change is now -1.73% CE, compared with -2.61% CE in our benchmark scenario. Valuing emissions reductions therefore substantially improves welfare, by $+0.88\%$ CE, although not enough to offset the average losses from the carbon tax. Future work could consider location-specific climate damages, allowing welfare effects to vary with regional exposure to climate risks as in Fried (2026).

Interaction of damage with Section 5. If we combine the valuation of climate damage

[12] French territorial emissions account for 1.01% of global emissions, while its carbon footprint represents 1.43% (see 2023 national accounts from Insee and Friedlingstein et al. (2024)).

[13] If only French emissions decline by 10% while the Rest of the World remains on the business-as-usual path, global temperature decreases by just 0.002 °C in 2100.

(+0.88% CE) with the different transfer scenarios in Section 5, we find that households in every income and geographic groups may in fact support the transition (except rural households in scenarios 2 and 3), as their welfare change is positive.

Valuing in-kind benefits. To isolate the distributive effects of the carbon tax, our baseline simulations assume that carbon tax revenues finance wasteful public spending, G. In practice, however, public expenditures generate social benefits. We therefore allow G to enter household utility separably: $\mathcal{G} = \chi_{\mathcal{G}} \sum_{t=0}^{\infty} \beta^t \ln G_t$. $\chi_{\mathcal{G}}$ is calibrated so that, at $G = 0.23$, the marginal utility of public spending equals the marginal welfare cost of raising labor income taxes, which yields $\chi_{\mathcal{G}} = 0.38$. With this new specification, the average welfare change is -1.05% CE, compared with -2.61% CE when public spending is not valued by households. Valuing G therefore substantially improves welfare, by +1.6% CE, although not enough to offset the losses from the carbon tax: the average welfare change remains negative in every location and income quintile. More broadly, the valuation and composition of public spending are likely heterogeneous across households, which could lead to different distributional outcomes. In the context of the carbon transition, targeted public investments in transportation and energy efficiency in rural areas could help mitigate the spatially uneven burden of carbon taxes.

7 Conclusion

In this paper, we study the distributive effects of carbon taxation with a focus on spatial heterogeneity. Using French household surveys and matched employer–employee data, we document large spatial differences in exposure to carbon policy: rural households spend 2.8 times more on fossil fuels than urban households and work in firms that emit 2.7 times more greenhouse gases. We incorporate these facts into a spatial heterogeneous-agent model with income risk, savings, housing tenure, and endogenous migration across segmented housing and labor markets.

We show that carbon taxes impose substantially larger welfare losses on rural households. In our benchmark scenario, their losses are 56% higher than those of households in Paris. While uniform or income-based transfers significantly reduce inequality across income groups, they leave large disparities across locations. Equalizing the burden of the carbon tax across both income and geography requires location-specific transfers. These results highlight the importance of accounting for spatial heterogeneity when designing carbon tax policies, particularly as the EU-ETS2 for household heating and transport becomes operational in 2027.

This work opens several avenues for future research. We focus on transfer policies, as they play a central role in addressing distributional concerns and enhancing political feasibility.

However, future studies could explore alternative uses of carbon tax revenues within our framework, such as reducing distortionary taxes or financing clean technologies, especially in rural areas. Finally, our findings indicate that mobility frictions, such as homeownership and migration costs, play a key role in shaping the distributive effects of carbon taxation, highlighting the need for further empirical work to better quantify these mechanisms.

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Appendix

Table of contents

A Descriptive Evidence

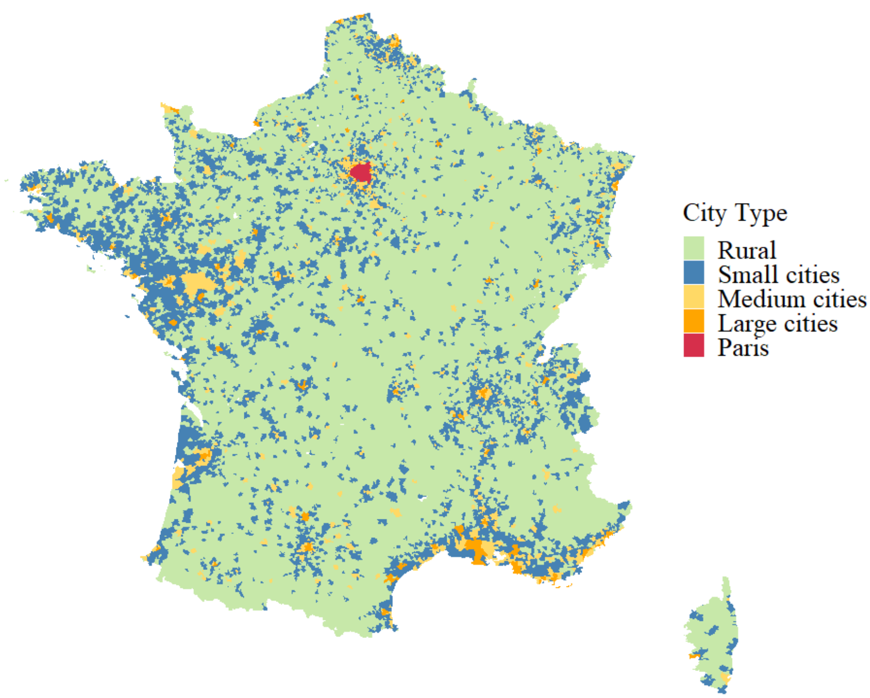
A.1 City types

Our categorization of city types is as follows:

- Rural areas: Fewer than 2,000 inhabitants.
- Small cities: Between 2,000 and 20,000 inhabitants.
- Medium cities: Between 20,000 and 50,000 inhabitants.
- Large cities: More than 50,000 inhabitants.
- Paris: The Parisian agglomeration, including the departments 75, 92, 93, and 94.

We favor this categorization because the population is uniformly distributed across these locations, according to the latest 2021 French Census. We check that we recover a similar distribution in our administrative datasets used in the following sections (BTS and fiscal declarations from households). Figure 10 provides a map of France illustrating these categories, using 2024 Insee geographical code.

Figure 10: Spatial distribution of city types, France



Notes. We have 34,998 observations with a Insee geographical code.
Sources. Population data downloaded from `https://www.data.gouv.fr/` using 2024 Insee geographical code and 2021 French Census data.

A.2 Households: energy consumption patterns

Energy share and geography: Table 2 shows the energy, fossil and electricity shares (in % of total consumption expenditures), by living area and income quintile. We decompose energy use by two categories: energy for housing purposes (and we show the share of population living in a house and the size of living spaces in squared meters) and energy for transports (with the share of car owners, the average number of vehicles per households, and the share of households using a car to commute). Table 3 presents average consumption in energy, fossil fuel, and electricity in euros.

Table 2: Descriptive statistics: households consumption

Variable	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
energy share	12.1	10.6	10.0	7.9	5.7	10.0	10.2	9.8	8.9	7.5
fossil fuel share	8.1	6.7	6.3	4.9	3.0	5.8	6.4	6.4	5.7	4.6
electricity share	4.0	3.9	3.7	3.0	2.7	4.2	3.8	3.4	3.2	2.9
energy for housing	6.3	5.8	5.4	4.3	3.6	6.0	5.8	5.2	4.7	4.1
% living in a house	94.4	80.2	67.7	41.2	22.2	43.7	54.4	62.3	63.4	63.9
size of living space (in m^2)	105.6	94.8	81.4	73.2	64.0	72.5	78.2	85.0	92.2	108.6
energy for transports	5.8	4.8	4.6	3.6	2.1	4.0	4.4	4.7	4.2	3.4
% car owners	93.3	89.9	85.9	77.9	59.6	63.0	76.6	86.2	88.9	88.8
# of vehicles per hhs	1.6	1.5	1.3	1.1	0.8	0.8	1.1	1.3	1.5	1.5
% using cars (commute)	47.5	47.5	44.6	42.0	25.0	23.5	36.8	45.8	51.8	49.3

Sources. size of living space coming from 2017 Fideli: over 26 millions observations. All over variables are from 2017 BdF: 16,739 households, weighted using survey weights.

Table 3: Annual mean households energy consumption, in euros

Consumption in €	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
energy	3729	2881	2606	2098	1824	1737	2173	2500	2748	3146
fossil fuel	2191	1827	1634	1297	954	1006	1365	1623	1768	1923
electricity	1088	1054	972	801	870	731	808	877	980	1233
total consumption	27103	27226	26093	26403	31807	17291	21351	25434	30852	42121

Sources. 2017 BdF: 16,739 households, weighted using survey weights.

Energy share and age: Table 4 shows the variable described above, by age groups. We find that age also correlates with energy consumption, mostly because of housing expenditures. This is why we add it as a control in our regressions. Yet, it appears that the fossil fuel share is roughly flat across age groups.

Table 4: Descriptive statistics: age groups

Variable	**<30**	**30-39**	**40-49**	**50-59**	**60-69**	**>70**
energy share	7.3	8.1	8.4	9.4	9.9	10.3
fossil fuel share	4.5	5.2	5.4	6.1	6.1	5.9
electricity share	2.8	2.9	3.0	3.4	3.8	4.4
energy for housing	3.4	3.8	4.3	4.9	5.7	7.3
% living in houses	23.4	50.6	59.0	64.2	67.9	65.2
energy for transports	3.9	4.2	4.1	4.5	4.2	3.0
% of car owners	68.5	82.1	86.2	86.8	84.7	72.1
# of vehicles per hhs	1.0	1.3	1.4	1.5	1.3	0.9
% using cars (commute)	51.5	63.6	65.3	59.8	15.6	1.7

Sources. 2017 BdF: 16,739 households, weighted using survey weights.

Indirect emissions by income and regions: In our model, we allow for heterogeneous household consumption of energy and fossil fuels, but we assume that the indirect emissions intensity associated with the consumption good c is the same across households. In other words, each unit of c generates the same amount of indirect emissions in every region. Table 5 reports the consumption of different emissions-intensive goods in each region.

Table 5: Annual mean households consumption of emission-intensive goods, in euros

Consumption in €	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
meat	1095	1021	956	877	929	692	877	951	1049	1220
coffee & chocolate	122	125	91	95	106	64	90	107	110	155
dairy products	648	618	525	531	554	409	511	552	631	738
electronics	1209	1204	1158	1139	1217	908	1011	1124	1284	1547
plane trips	87	102	141	135	355	111	67	93	158	350
total CO_2eq-intensive goods	3161	3070	2871	2777	3161	2184	2556	2827	3232	4010
total consumption	27103	27226	26093	26403	31807	17291	21351	25434	30852	42121

Sources. 2017 BdF: 16,739 households, weighted using survey weights.

Energy shares in other countries: Table 6 provides the energy share by living area and income quintile for some countries, using Eurostat 2020 Household Budget Surveys (HBS) that harmonizes micro-data for European countries. The data is from 2020, except for the UK, which is from 2015. Italy does not have quintile distribution data. “Towns” includes both towns and suburbs. For the US, we use the Consumer Expenditure Survey (CES) 2023 for the US, and the category > 1M covers cities with populations over 1 million.

In both datasets, we can recover average energy shares by income quintiles and by city sizes. Energy consumption is decomposed between housing and transport costs. Note that in the HBS dataset, we cannot distinguish fossil fuels from other transport costs such as repairs or parking fees. We find that rural areas consistently exhibit higher energy shares compared to towns and cities across all countries.

Table 6: Energy share in total consumption (%) for several countries

	Rural	**Towns**	**Cities**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
France (sum)	**11.8**	**10.3**	**7.9**	**10.3**	**10.0**	**10.3**	**9.8**	**8.6**
electricity & gas (housing)	5.2	4.6	3.6	5.5	4.8	4.5	4.2	3.6
transport costs incl. fuels	6.6	5.7	4.3	4.8	5.2	5.8	5.6	5.0
Germany (sum)	**13.7**	**12.6**	**9.8**	**12.7**	**12.3**	**12.1**	**11.9**	**11.1**
electricity & gas (housing)	5.7	5.3	5.0	7.7	6.5	5.7	5.1	3.9
transport costs incl. fuels	8.0	7.3	5.7	4.0	5.8	6.4	6.8	7.2
Italy (sum)	**14.1**	**12.2**	**9.8**	–	–	–	–	–
electricity & gas (housing)	6.7	5.8	5.0	–	–	–	–	–
transport costs incl. fuels	7.4	6.4	4.8	–	–	–	–	–
Netherlands (sum)	**10.4**	**10.2**	**9.1**	**7.4**	**8.4**	**9.3**	**9.6**	**11.0**
electricity & gas (housing)	4.5	4.2	3.8	5.0	4.5	4.1	3.9	3.4
transport costs incl. fuels	5.9	6.0	5.3	2.4	3.9	5.2	5.7	7.6
Spain (sum)	**14.6**	**11.0**	**8.5**	**10.2**	**11.0**	**10.9**	**10.0**	**9.1**
electricity & gas (housing)	5.1	4.2	3.9	5.4	4.8	4.5	4.2	3.6
transport costs incl. fuels	7.5	6.8	4.6	4.8	6.2	6.4	5.8	5.5
UK (sum)	**14.3**	**12.8**	**10.2**	**11.2**	**12.6**	**12.2**	**12.5**	**11.7**
electricity & gas (housing)	5.4	4.8	4.9	7.6	6.5	5.2	4.5	3.7
transport costs incl. fuels	8.9	8.0	6.3	3.8	6.1	7.0	8.0	8.0
US (sum)	**8.3**	**7.1**	**5.7**	**8.8**	**8.9**	**7.7**	**6.9**	**4.8**
electricity & gas (housing)	3.9	3.3	2.8	4.9	4.5	3.6	3.1	2.2
fossil fuels (transports)	4.4	3.8	2.9	3.9	4.4	4.1	3.8	2.6

Sources. Eurostat 2020 Household Budget Surveys (HBS) for European countries, 2023 Consumer Expenditure Survey (CES) for the US.

Therefore, the dominance of geography over income extends to many countries, as shown 6 above. In Germany, Spain, the Netherlands, and the United Kingdom, the energy share of total expenditures is relatively flat across income quintiles, with Q1-to-Q5 ratios of 1.1, 1.1, 0.7, and 1.0, respectively. However, the energy share in these countries varies significantly across living areas, with Rural-to-City ratios of 1.4, 1.1, 1.7, and 1.4, respectively. In the United States, geography also plays a key role in determining energy consumption (8.3% in rural areas versus 5.7% in cities with populations over 1 million). Income differences are more pronounced, with energy shares of 8.8% for Q1 compared to 4.8% for Q5. This contrast between the United States and Europe can be attributed to city structures and related transportation costs. While transportation expenses are higher for wealthier households in

Europe, the opposite is true in the United States, where even the lowest-income households allocate a substantial share of their expenditures to transportation.

A.3 Households: living spaces

We use the 2017 Fideli database to assess the size of living spaces according to income and spatial characteristics. Fideli (Fichier Démographique d'Origine Fiscale sur les Logements et les Individus) is a structured administrative dataset that links tax records on housing properties with declared income using fiscal identifiers for households and dwellings. The dataset provides detailed information on demographics, household composition, income levels, social benefits received, and geographic context, covering mainland France as well as all overseas departments. We use these data to construct Table 2, Table 7, and to derive calibration targets for housing size among renters and homeowners by city type.

Table 7: Households' size of living space, in m^2

Variable	**Rural**	**Small**	**Medium**	**Large**	**Paris**
Q1	93.4	78.8	68.1	61.6	53.1
Q2	96.3	82.9	71.2	64.4	56.0
Q3	102.0	90.6	77.6	69.6	57.4
Q4	110.0	99.8	85.7	77.4	60.5
Q5	130.3	120.7	106.3	98.6	77.9

Sources. 2017 Fideli: over 26 millions observations.

A.4 Firms: emission patterns

Data on sectoral emissions. To recover sectoral emissions, we use Insee national accounts that reports total emissions and emissions per euro of value-added for most sub-sectors of the French economy. As a robustness, we also compute emissions intensity using datasets from Bach et al. (2024) (mining and manufacturing), CITEPA (waste). We build a tCO_2eq per worker metric using annual value-added and employment levels from 2022 National Accounts. We find very heterogeneous results across sectors. Within manufacturing, 'Coke & refining' is the most intensive in emissions with $1,512$ tCO_2eq annual emissions per worker. 'Air transports' is the most intensive across all sectors with $2,379$ tCO_2eq per worker. In the services (except construction and transportation), firms emit on average 1.9 tCO_2eq per worker. A notable exception among the services are 'Rental and leasing activities' that emits 43.7 tCO_2eq per worker every year.

Administrative data on workers and firms. ***All employer - employee data* (BTS-Salariés)**. The BTS is an annual report that all companies employing salaried workers in France are required to submit. These reports contain numerous worker- and firm-level details, including wages, hours worked, job type, qualifications, pay periods, employment type (full-time/part-time), and both workers' and firms' geographical locations. The BTS dataset covers all employees, including those in public companies, local governments, and public hospitals. There exists a panel version of that repeated cross-section called *The All Employees Panel*. The latter has been tracking employees since 1976. Up to and including 2001, the sample size was approximately 1/24th, based on individuals born in October of an even-numbered year. From 2002 onwards, the sample has been doubled and covers around 3 millions individuals each year. We notably use the panel version to compute mobility rates by regions and quintiles.

Merging BTS micro data and sectoral emissions. From the BTS 2022, we assign to each worker i the average emissions intensity from its firm's f i.e. $\alpha_i = \alpha_f$. In each group (city or quintile), we then compute the average α_i i.e. $\frac{1}{\text{length}(q)} \sum_{i \in q} \alpha_i$. Those results are presented in Figure 2. For our extensive margin, we define emissions-intensive sectors as those with a tCO_2eq per worker above 5. This represents the 20% most emissions-intensive jobs. We present some additional descriptive statistics in Tables 8 and 9.

Table 8: Share of workers (%) in each sector, by geography and income quintile

Sector	**NAF Code**	**Emissions per worker**	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Agriculture	01-03	227.9	3.0	1.6	0.9	0.6	0.1	2.5	1.8	1.4	0.8	0.4
Industry	05–33	33.6	14.2	12.1	8.9	6.6	4.3	5.6	6.4	10.1	12.7	15.0
Energy	35	227.5	0.8	0.6	0.5	0.5	0.6	0.2	0.2	0.2	0.6	1.8
Water supply & waste	36–39	163.9	0.8	0.8	0.7	0.5	0.5	0.4	0.4	0.7	1.2	0.7
Construction, sales & repairs	41–47	4.1	20.8	20.5	18.2	17.0	16.6	20.9	19.7	22.2	18.3	14.9
Transportation & storage	49-53	62.6	5.4	5.3	5.3	4.5	4.6	3.4	4.1	5.8	7.4	4.9
Services	55–99	1.9	55.0	59.1	64.4	70.4	73.4	67.1	67.5	60.6	59.0	62.3
Sum	–	–	100	100	100	100	100	100	100	100	100	100

Notes. We use the 2022 cross-section of the BTS. We remove values below €1,000 annual and we merge individuals present more than once in the dataset, ending up with 31,836,096 observations.

In Table 8 we show the share of workers in each sector, by city types and by income quintiles. In Table 9, we show the counterpart statistics: share of each city type (and income quintile) within each sector. Both statistics go in the same direction: rural workers are over-represented in emissions-intensive sectors.

Table 9: Share of city type and income quintile by sector, % of workers

Sector	NAF Code	Emissions	Labor share	Rural	Small	Medium	Large	Paris	Q1	Q2	Q3	Q4	Q5
		$\frac{tCO_2}{\text{Workers}}$	% total	% sectoral workers					% sectoral workers				
Agriculture	**01-03**	**227.89**	**1.37**	**45.96**	**30.92**	**16.04**	**6.69**	**0.39**	**36.87**	**25.98**	**20.11**	**11.38**	**5.65**
Crop, animal production, hunting	01	250.58	1.22	46.57	30.37	15.93	6.79	0.35	38.78	26.77	20.05	10.18	4.23
Forestry and logging	02	26.86	0.09	52.29	25.92	15.77	4.97	1.06	20.43	18.15	20.85	25.63	14.94
Fishing and aquaculture	03	68.98	0.07	26.33	47.72	18.60	7.01	0.33	22.97	21.53	20.34	15.18	19.98
Industry	**5-33**	**33.58**	**9.93**	**30.35**	**32.10**	**21.21**	**11.13**	**5.21**	**11.29**	**12.87**	**20.30**	**25.44**	**30.09**
Mining & quarrying	5-9	18.27	0.07	42.55	30.35	16.70	6.98	3.42	6.59	9.83	17.51	36.10	29.98
Manufacturing	10-33	33.69	9.86	30.27	32.11	21.24	11.17	5.22	11.33	12.90	20.32	25.36	30.09
Paper & paper products	17	38.10	0.20	38.00	35.02	18.08	7.22	1.68	5.64	8.64	19.68	33.61	32.43
Coke & refining	19	1512.03	0.03	23.21	27.94	28.37	15.87	4.61	3.03	4.48	4.91	9.72	77.86
Chemicals & chemical products	20	140.90	0.50	26.95	30.04	22.51	10.40	10.10	6.38	8.60	12.97	21.80	50.25
Other non-metallic mineral prod.	23	208.94	0.35	38.45	32.14	18.87	7.39	3.15	7.39	10.36	20.31	30.41	31.54
Basic metals, metallurgy	24	267.47	0.26	35.28	33.25	21.67	8.76	1.04	4.91	7.58	16.52	32.67	38.32
Energy	**35**	**227.47**	**0.58**	**28.15**	**24.64**	**20.86**	**13.97**	**12.39**	**5.32**	**5.95**	**6.13**	**19.86**	**62.75**
Water supply & waste	**36-39**	**163.93**	**0.69**	**25.71**	**28.72**	**23.90**	**13.58**	**8.09**	**10.24**	**12.49**	**21.50**	**34.65**	**21.12**
Waste management	37-39	207.78	0.54	24.59	28.11	24.50	14.00	8.80	11.28	13.61	23.22	33.66	18.22
Construction, sales and repairs	**41-47**	**4.13**	**19.21**	**22.95**	**28.13**	**23.61**	**14.90**	**10.40**	**21.84**	**20.62**	**23.14**	**19.03**	**15.38**
Transportation & storage	**49-53**	**62.61**	**5.10**	**22.35**	**27.34**	**24.74**	**14.70**	**10.87**	**13.30**	**16.11**	**22.65**	**28.90**	**19.03**
Land transport & pipelines	49	22.54	2.84	24.04	27.17	23.80	14.08	10.91	16.44	18.17	20.39	29.81	15.20
Water transport	50	2378.54	0.08	14.65	27.38	26.02	27.77	4.17	15.96	19.81	15.49	15.23	33.51
Air transport	51	321.26	0.20	12.81	24.15	26.89	12.32	23.82	4.38	11.16	20.28	27.26	36.93
Services (other)	**55-99**	**1.90**	**63.11**	**18.46**	**24.61**	**24.13**	**18.76**	**14.03**	**21.35**	**21.51**	**18.87**	**18.63**	**19.65**
Rental and leasing activities	77	43.73	0.42	19.39	27.26	25.23	15.74	12.38	16.85	19.13	21.93	21.99	20.11

Notes. We use the 2022 cross-section of the BTS. We remove values below €1,000 annual and we merge individuals present more than once in the dataset, ending up with 31,836,096 observations.

A.5 Predicted energy shares and emissions

OLS Regressions. Table 2 displays average energy shares for income quintile and location, but there is a correlation between these dimensions. This is why we regress our variables of interest using the following OLS regression:

$$y_i = \alpha + \sum_{q=1}^{5} \beta_q \mathbb{I}_{Q_i=q} + \sum_{k=1}^{5} \gamma_k \mathbb{I}_{C_i=k} + \mu * \text{Controls}_i + \epsilon_i \tag{8}$$

with y_i either individual consumption share or the emissions intensity of the worker, Q_i income quintile groups and C_i city-size groups (as defined in Section 1.1). We control by age and household's size when regressing for consumption patterns. Results of our regression are presented in Table 10 below. We use the regression coefficients to build average energy consumption shares in Figure 1 and average emissions per worker in Figure 2. One can interpret our results as the mean energy share (or mean emissions per worker) in each group (city type or income quintile) if the group had the same characteristics as the whole population. As a robustness, we use different estimates of sectoral level emissions from Bach et al. (2024) and the CITEPA in column (5), while column (4) uses sectoral-level estimates from national accounts. In both columns, we used the sector of the establishment since the biggest firms may operate in several sectors with different emissions intensities. As an additional robustness check, we also provide the same regressions using firm-level sectoral emissions in column (6).

Table 10: Regressions

	y_i: consumption share BdF 2017			y_i: emissions per worker BTS 2022		
	(1) Energy	(2) Fossil fuel	(3) Electricity	(4) Nat. Acc.	(5) IPP	(6) Firm-level
Intercept	12.00***	6.77***	5.23***	18.03***	20.37***	17.77***
	(0.32)	(0.29)	(0.16)	(0.04)	(0.05)	(0.04)
Q2	−0.72***	0.15	−0.88***	−0.87***	−0.66***	−0.94***
	(0.20)	(0.18)	(0.10)	(0.05)	(0.05)	(0.05)
Q3	−1.05***	0.21	−1.27***	−0.58***	0.35***	−0.71***
	(0.20)	(0.18)	(0.10)	(0.05)	(0.05)	(0.05)
Q4	−1.65***	−0.04	−1.61***	1.32***	3.77***	1.01***
	(0.20)	(0.18)	(0.10)	(0.05)	(0.05)	(0.05)
Q5	−2.28***	−0.51**	−1.77***	7.55***	11.30***	7.65***
	(0.20)	(0.18)	(0.10)	(0.05)	(0.05)	(0.05)
Small	−1.89***	−1.79***	−0.10	−4.13***	−5.17***	−4.02***
	(0.22)	(0.20)	(0.11)	(0.04)	(0.05)	(0.05)
Medium	−2.50***	−2.01***	−0.49***	−6.41***	−8.32***	−6.26***
	(0.22)	(0.20)	(0.11)	(0.04)	(0.05)	(0.04)
Large	−4.97***	−3.68***	−1.28***	−7.88***	−10.51***	−7.71***
	(0.17)	(0.15)	(0.08)	(0.05)	(0.05)	(0.05)
Paris	−7.11***	−5.54***	−1.56***	−12.17***	−16.00***	−11.85***
	(0.21)	(0.19)	(0.11)	(0.05)	(0.05)	(0.05)
Age	0.06***	0.03***	0.02***	–	–	–
Household size	−0.11*	0.16***	−0.27***	–	–	–
Observations	16,739	16,739	16,739	31,836,096	31,836,096	31,614,291

Notes. This table report results of Equation (8). In columns (1) to (3), we use survey weights. Columns (2) and (3) are used in Figure 1. Column (4) is used in Figure 2. In BdF 2017, we only keep observations with strictly positive disposable income. In BTS 2022, we only keep workers with annual net wage declared above €1,000. Column (4) uses sectoral emissions estimates from national accounts at the establishment-level. Column (5) uses sectoral emissions estimates from Bach et al. (2024) and CITEPA, again at the establishment-level. Column (6) uses sectoral emissions estimates from national accounts at the firm-level.
*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

A.6 Spatial distribution of emissions patterns

Spatial distribution of households' fossil fuels consumption: Leveraging the complete set of fiscal declarations from French households in 2021, we estimate the spatial distribution of fossil fuel consumption. The methodology involves the following steps:

1. Using the 2017 BdF survey, we regress the fossil fuel share on variables that are also available in the fiscal declarations: disposable income, age of the household reference person, household size, and city type. To mitigate the influence of outliers, we limit the analysis to households with a fossil fuel share below 50% (5 standard deviations above the mean).
2. Based on this regression model, we predict the fossil fuel share for each household in the fiscal declarations dataset. We retain households with an annual income above €$2,100$, and for which a city type can be assigned. This yields 36,582,417 household-level observations.
3. Finally, we calculate the average fossil fuel share for each Insee geographical/city code (34,987 areas) and present the spatial distribution in panel *a* Figure 3.

Spatial distribution of firms' sectoral emissions. Using the 2022 BTS, we can visualize emissions per worker by geographical location at a very granular level. In panel *b* Figure 3, we present a map showing the average emissions per worker at the local scale. We have 31,836,096 worker-level observations, which are aggregated into 34,607 geographical units.

B Algorithm

The main challenges of this paper are the heterogeneous-agent structure, the discrete location choice and the high number of guesses. In this section, we detail the algorithms used at the steady state, for the calibration and during the transition. Each steady state takes 30 seconds to compute on a personal computer, and a few minutes for a non-linear transition between two distinct steady states. Computing the Jacobian used to update transition's guesses take up to 30 minutes. The entire code has been written from scratch on Matlab.

Heterogeneous-agent structure. Our state-space for asset, income, geography and housing type is $\mathbb{S} = \mathbb{A} \times \mathbb{Z} \times \mathbb{K} \times \mathbb{H}$. We discretize $\mathbb{A}$ over an exponential grid of 80 points between 0 and 70, $\mathbb{Z}$ over 7 points using Tauchen (1986) method, $\mathbb{K} = \{1, 2, 3, 4, 5\}$, and $\mathbb{H} = \{0, 1\}$ which gives us 5,600 grid points. We solve the household decision using value function iteration (VFI). The key variable of choice for the household is the implicit utility $\mathcal{C}(a, z, k, k)$: given $\mathcal{C}, k', h'$ and the first-order conditions, the households can choose its consumption c, e^h, N^h, F^h and labor supply l, and the budget constraint gives the saving choice a' as a residual. For simplicity, we denote $\Omega = (a, z, k, h)$ the household's initial state variables. Similarly $\Omega' = (a', z', k', h')$ households' next period state variables. To solve the VFI, we follow these steps:

1. for each choice $k' \in \mathbb{K}, h' \in \mathbb{H}$, use a golden-section algorithm to find the implicit utility $\mathcal{C}^{k',h'}(\Omega)$ such that $a' = 0$, to obtain a lower bound for the maximization of the utility.
2. guess the expected value function $f(\Omega) = \mathbb{E}[V(\Omega)]$.
3. for each choice $k' \in \mathbb{K}, h' \in \mathbb{H}$, use a golden-section algorithm to find the implicit utility $\mathcal{C}^{k',h'}(\Omega)$ that maximizes the value function $\mathcal{C}^{k',h'}(\Omega) + \beta f(\Omega')$.
4. using Gumbel trick described below, find the new value function $V(\Omega)$.
5. using spline interpolation over $V(\Omega)$, compute the new guess for the value function $f(\Omega)$.
6. use the Howard's improvement: for 30 iterations, iterate the f guess without optimizing, taking $f^{new}(\Omega) = u^{k',h'}(\Omega) + \beta f(\Omega)$.
7. compare the new value function f^{new} with the guess $f(\Omega)$: if the Euclidian norm of the difference is above 10^{-8}, replace f by f^{new} and go back to step 3.

Once we have the decision rule, we compute the transition matrix M between Ω and Ω'. If $d(a, k, z)$ is our column measure of density over the state space, we compute $d' = Md$. This means that the row i of d is associated with the column i of M. Therefore, for each i of the state space, we fill the column i of M with $2 * 7 * 5 * 2$ values that are the products of:

- **a**: for the household's decision $a'(\Omega)$, we put a' on our grid $\mathbb{A}$, by computing weights

ω^- and ω^+ depending on the distance between a' and the inferior (a^-) and superior (a^+) points of the grid, and we put the values ω^- and ω^+ at every rows a^- and a^+ of the state space.

- **z**: using the Tauchen weights, we put the probability $P(z \to z')$ at every rows z'.
- **k**: using the migration probability $\mathbb{P}(k \to k')$ computed during the Gumbel trick (see below), we put these probabilities for every rows k'.
- **h**: using the housing probability choice $\mathbb{P}(h \to h')$ computed during the Gumbel trick (see below), we put these probabilities for every rows h'.

Note that we use a sparse matrix M, as most coordinates are empty. Finally, we compute $d' = Md$ until every row of $|d' - d|$ is lower than 10^{-8}, *i.e.* when we obtain the stationary density given the decision matrix M.

Discrete location choice. We follow Ferriere and Navarro (2025) for the implementation of discrete choice with preference shocks drawn from an extreme-value distribution. Denote $V_t^{k',h'}(\Omega)$ the value function for the household at the grid point (Ω) choosing the future location k' and future housing tenure h'. Recall that when switching location $k \neq k'$, households must start next period as a renter. Let $\epsilon_{k',h'}$ the preference shock for each location $\times$ housing type state (k', h') possible, and assume the vector $\overrightarrow{\epsilon} = \{\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4, \epsilon_5, \epsilon_6\}$. Then the complete value function is the expectation of all (k', h')-value function, taken over $\overrightarrow{\epsilon}$:

$$V_t(\Omega) = \mathbb{E}_{\overrightarrow{\epsilon}}\left[\max_{k,h}\left\{V_t^{k',h'}(\Omega)\right\}\right] = \varrho \ln\left(\sum_{\{k',h'\}\in\mathbb{K}\times\mathbb{H}} \exp\left(\frac{V_t^{k',h'}(\Omega)}{\varrho}\right)\right)$$

where the last equality derives from assuming that $\epsilon_{k',h'}$ follows a Gumbel distribution with variance ϱ. The probability of choosing location $\times$ housing type (k', h') is given by:

$$\mathbb{P}_t^{k',h'}(\Omega) = \frac{\exp\left(\frac{V_t^{k',h'}(\Omega)}{\varrho}\right)}{\sum_{\{k',h'\}\in\mathbb{K}\times\mathbb{H}} \exp\left(\frac{V_t^{k',h'}(\Omega)}{\varrho}\right)} = \exp\left(\frac{V_t^{k',h'}(\Omega) - V_t(\Omega)}{\varrho}\right)$$

High number of guesses. We need $n_g = 14$ guesses to solve our model, at the steady state and during the transition: interest rate R (asset market), total electricity N (electricity market), housing prices$\{p_1^H, p_2^H, p_3^H, p_4^H, p_5^H\}$ (segmented housing markets), local outputs $\{Y_1, Y_2, Y_3, Y_4, Y_5\}$ (segmented labor markets), carbon tax revenue CTR (government budget constraint) and a scaling parameter to rebate profits according to households' productivity levels. For the calibration procedure, we use more than 40 guesses, as we add parameters as guesses and calibration targets as clearing conditions.

To find the equilibrium values for our guesses at the steady state, we use a quasi-Newton algorithm, improved with the Broyden method. Denote $\mathbf{x}$ the column vector of our guess variables, and f the function that associates the vector of guesses to the column vector of errors $\mathbf{e}$ in each clearing conditions, so that $f(\mathbf{x}) = \mathbf{e}$. f is the central function, that computes the optimality conditions for firms, governments, households and the measure. We use the following steps:

1. guess an initial vector $\mathbf{x}_0$, and compute the error $\mathbf{e}_0 = f(\mathbf{x}_0)$.
2. for each guess i, create the vector $\mathbf{x}_0^i$ with $\mathbf{x}_0^i(i) = \mathbf{x}_0(i) + \epsilon$ (with $\epsilon = 10^{-4}$) and $\mathbf{x}_0^i(\bar{i}) = \mathbf{x}_0(\bar{i})$, and compute the error $\mathbf{e}_0^i = f(\mathbf{x}_0^i)$.
3. create the Jacobian matrix M of size n_g^2 that relates a change of each guess to a change in each clearing condition. The column i is the vector $\mathbf{e}_0^i - \mathbf{e}_0$.
4. iterate the guess using $\mathbf{x}^{new} = \mathbf{x} + \alpha$, with $\alpha = -M^{-1} * \mathbf{e} * d$, with d a dampening factor (usually equal to 1, can be lower if the initial guess is far for the equilibrium). Denote $\mathbf{e}^{last} = \mathbf{e}$ the error.
5. compute $e^{new} = f(\mathbf{x}^{new})$.
6. modify the Jacobian matrix using the Broyden algorithm: $(M^{-1})^{new} = M^{-1} + \frac{(\alpha-\theta)(\alpha' M^{-1})}{\alpha'\theta}$, with $\theta = M^{-1}(\mathbf{e} - \mathbf{e}^{last})$. If the code does not converge, it is also possible to recompute, every t iterations, the "true" Jacobian of step 3.
7. if $\max|\mathbf{e}| > 10^{-5}$, go back to step 4.

For the non-linear transition, we use the same method of guessing a path for our variables and iterating it using a quasi-Newton algorithm. First, we compute the initial and final steady state, as we consider a permanent increase in carbon tax.

Second, we compute the Jacobian of our system around the final steady state. This means that we compute the effect of a shock at any time period t^{schock} of the transition (140-1 in our experiment), of any variable i (14), on any clearing condition j (14), at any time $t^{clearing}$ (139), leading to a matrix $J = 1894 \times 1984$. To compute this object efficiently, we use parallel computation (as any variable can be shocked independently), sparse vectors, and the fake-news algorithm developed by Auclert, Bardóczy, et al. (2021). While formally dependent on the final steady state considered, the matrix J can be used to compute transitions towards other steady states (possibly with a dampening factor), as it only provides a new guess for the non-linear transition, and not the real path.

Third, we use the following algorithm to compute the non-linear transition:

1. guess an initial path $\mathbf{X}$ of size $n_g \times (T-1)$ for our guess variables.
2. starting from period $T-1$, compute the optimal backward decision for households, and the firms' and government optimality conditions.

3. create the transition matrix as explained above for each period, and iterate forward from 1 to $T-1$ to obtain the measure and the aggregate variables.
4. compute the path of errors $\mathbf{E}$ of size $n_g \times (T-1)$ for the market clearing condition.
5. iterate the guess path using $\mathbf{X}^{new} = \mathbf{X} - J^{-1}\mathbf{E}$.
6. if $\max |\mathbf{E}| > 10^{-3}$, go back to step 2.

C Calibration

Table 11: Table of parameters

Parameter	Description	Value	Notes and targets
Households			
β	Discount factor	0.958	$\frac{a}{\text{GDP}} = 4.5$
θ	Intertemporal ES	1	Kaplan, Moll and Violante (2018)
χ	Taste for housing	0.2	Rents = 16% of expenditures
ν	ES between housing and $\mathcal{C}$	1/1.25	Kaplan, Mitman and Violante (2020)
ϕ	Scaling labor disutility	3.03	GDP = 1
ψ	Inverse Frisch elasticity	1	Kaplan, Moll and Violante (2018)
σ	ES between c and e^h	0.2	Estimated in Appendix C
Λ	Energy share	0.108	Energy share in consumption = 9.5%
ϵ	Non-homotheticity energy	0.55	Energy exp. across income quintiles
$\bar{e}(k)$	Energy incompressible use	$[0.04, 0.03, 0.03, 0.01, 0]$	Energy share across types
$\gamma_h(k)$	Fossil share	$[0.82, 0.79, 0.79, 0.78, 0.71]$	Fossil share in consumption by region
ϵ_h	ES between F^h and N^h	1.5	Authors choice
ω	taste for homeownership	1.06	Share of homeowners = 59.5%
$s^r(k)$	size home for renters	$[82, 71, 65, 61, 54]$	2017 Fideli
$s^o(k)$	size home for owners	$[112, 106, 96, 89, 78]$	2017 Fideli
$\kappa^{\text{mig}}(k, k')$	Migration costs	see Figure 12	Empirical migration matrix
δ^h	Depreciation housing	0.5	Kaplan, Mitman and Violante (2020)
κ^{sell}	Selling cost	0.1	Kaplan, Mitman and Violante (2020)
$\rho_{\mathcal{G}}$	Gumbel shock variance	0.1	Income heterogeneity, aggregate
$\underline{a}$	Borrowing constraint	0	Authors' choice
Firms			
p^F	Price of fossil fuel	0.267	Share of fossil fuel imports = 4%
$\omega_y(k)$	Energy share	$[0.29, 0.20, 0.16, 0.14, 0.05]$	Share each regional firm/total emissions
σ_y	ES between e^y and (K^Y, L^Y)	0.05	Fried (2018)
α	Capital share	0.2904	Cette, Koehl and Philippon (2019): $\frac{wl}{GDP} = 65\%$
γ_y	Share of fossil in Y mix	0.869	Firms' share in total emissions = 75%
ϵ_y	ES between F^y and N^y	1.5	Fried (2018)
ζ	Share capital in N	0.978	$\frac{F^N}{F} = 1\%$
δ^F	Fossil price elasticity	0	Choice, see Section 6
$\eta(k)$	operating cost rental	$[0.016, 0.011, 0.007, 0.011, 0.010]$	Share of homeowners (2017 Fideli)
$\Xi(k)$	Housing supply parameter	$[0.55, 0.54, 0.33, 0.21, 0.23]$	Population share by region (2017 BdF)
δ_H	Housing supply elasticity	0.2	Choice, see Section 3
Government			
$\lambda, \tau, \bar{T}$	Labor tax and transfers	0.096	Labrousse and Perdereau (2025)
τ^{VAT}	VAT tax rate	12.9%	Labrousse and Perdereau (2025)
τ^k	Capital income tax	9.02%	Effective rate in Auray et al. (2022)
τ^{prop}	Property tax	1%	Estimated, see Section 3

C.1 Data on income

For Figure 4, we use 2017 BdF. For Figure 5.a, we use the average disposable income by decile from 2021 RPM that we reproduce in Table 12. For Figure 5.b, we use BdF 2017 as reproduced below in Table 13. We also looked at the joint distribution in the 2021 fiscal declarations and found very similar results.

Table 12: Revenues and taxes by income decile (thousand euros)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Primary income	10.5	15.9	21.0	25.9	31.3	36.4	42.2	49.5	60.4	133.1
Net labor income	4.8	9.5	13.5	17.5	21.7	25.7	30.0	35.4	42.0	69.2
Net financial income	1.8	2.1	2.8	3.2	3.7	4.4	5.4	6.6	9.6	52.3
Sum of taxes	-4.8	-5.6	-6.7	-7.9	-9.2	-10.5	-12.1	-14.5	-18.5	-46.3
Taxes on products and production	-4.2	-4.7	-5.1	-5.6	-6.3	-6.7	-7.3	-8.0	-9.4	-12.7
Taxes on income and wealth	-0.6	-1.0	-1.6	-2.3	-3.0	-3.7	-4.9	-6.5	-9.0	-33.6

Table 13: Geographical composition of each revenue decile (%)

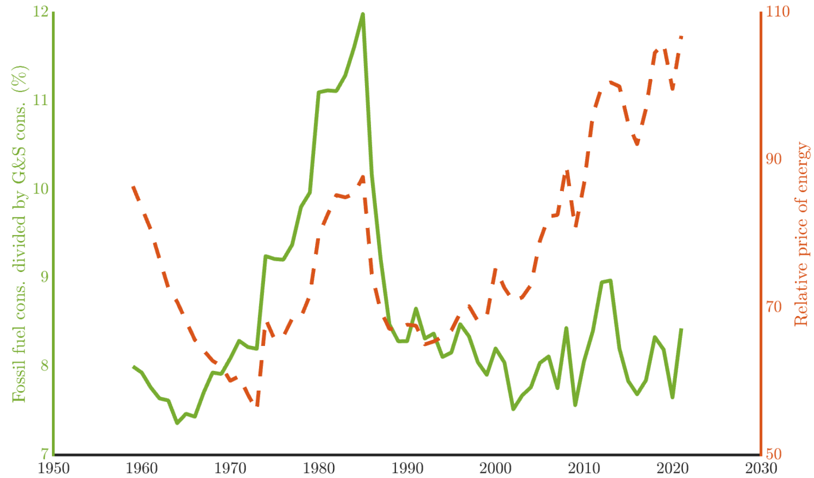
	Q1	Q2	Q3	Q4	Q5	Mean
Rural	17.7	24.7	25.6	26.8	20.4	23.5
Small cities	21.0	25.9	27.0	28.7	25.5	26.0
Medium cities	22.3	19.8	18.7	17.6	16.8	18.5
Large cities	20.8	14.9	13.05	11.3	12.2	13.4
Paris	18.2	14.7	15.6	15.7	25.0	18.5
Sum	100	100	100	100	100	100

Sources. BdF 2017: 16,739 households, weighted using survey weights.

C.2 Household energy consumption: estimation of σ

In Figure 11, we use French longitudinal aggregate data taken from 2022 national accounts. As explained in Hassler, Krusell and Olovsson (2021), the share of energy in total consumption comoves with the relative price of energy. This would not happen if energy and goods consumption were perfect substitutes.

Figure 11: Consumption ratio ($\frac{e^h}{c}$) and relative price of energy (p^h)



With Comin, Lashkari and Mestieri (2021) preferences, the elasticity of substitution between goods of different sectors is constant, *i.e.*

$$\frac{\partial \ln(c/e^h)}{\partial \ln(p^h)} = \sigma$$

Thus, we estimate σ through a simple OLS estimation:

$$\Delta \ln(e_t^h) - \Delta \ln(c_t) = -\sigma \Delta \ln(p_t^h) + \epsilon_t$$

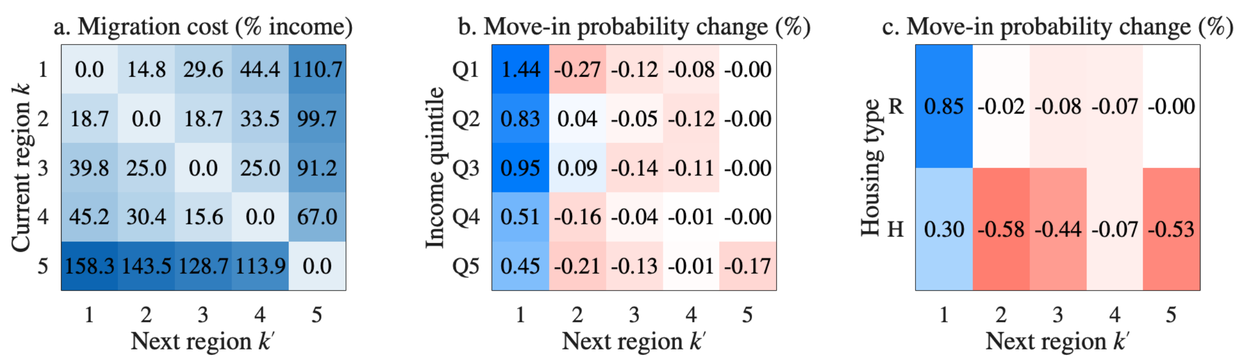
We get $\hat{\sigma} = 0.2$, significant at the 5% level. From the graph, we can isolate two periods. It seems that before 1990, the consumption ratio comoved more with p^h than after. Restricting our estimation to the 1959-1990 period, we get $\hat{\sigma} = 0.28$ significant at the 5% level. Taking only the 1990-2021 period we get $\hat{\sigma} = 0.08$ not significantly different from zero. Adding an intercept to the regression always yields a zero for the constant term. As Hassler, Krusell and Olovsson (2021) that use U.S. data, we find low short-run elasticity between energy and non-energy inputs in French data. In our benchmark calibration, we decide to set $\sigma = 0.2$, which is in the range of Casey (2024) pointing out that Cobb-Douglas functions vastly over-estimate transitional energy adjustments, and Golosov et al. (2014) that use such a framework.

C.3 Migration parameters

How do our migration costs relate to the empirical literature? There are two main approaches in the literature to discipline migration costs in models. The first is to estimate monetary moving costs directly from data or through structural modeling. For instance, Kennan and

Walker (2011) estimate an average moving cost of $312,000, equivalent to approximately 600% of annual income. However, this is a hypothetical cost, as it reflects the case of an individual being forced to move to a random location; in practice, households choose destinations, typically reducing the cost. Similarly, Artuç, Chaudhuri and McLaren (2010) estimate sectoral migration costs ranging from 2 to 13 times the average annual wage. Other studies, such as Bryan and Morten (2019) and Clemens, Montenegro and Pritchett (2019), employ lower values, between 15% and 50% of annual income. Panel *a* of Figure 6 presents our migration cost matrix, expressed as a share of mean household disposable income. We highlight three important features. First, averaging across the entire matrix (excluding the diagonal), and using population weights, the average (hypothetical) migration cost is 62% of annual income. This hypothetical cost is the average an individual would have to pay to move to an arbitrary location. If we instead average over observed migration flows, we find that migrating households pay 34% of their income on average. Second, migration costs vary substantially depending on the origin region. Averaging across each row, *i.e.* $\sum_{k'\neq k}\kappa(k,k')/4$, we obtain the hypothetical cost of moving from region k to a randomly chosen region. These values are 50%, 43%, 45%, 40%, and 130% for rural, small, medium, large, and Paris, respectively. Third, migration costs also depend on the destination region. Averaging across each column, *i.e.* considering the cost of migrating to region k' from a randomly selected origin, yields values of 65%, 53%, 48%, 54% and 92% for rural, small, medium, large, and Paris, respectively. This suggests that the larger and more urbanized, the higher the associated migration cost.

Figure 12: Migration parameters



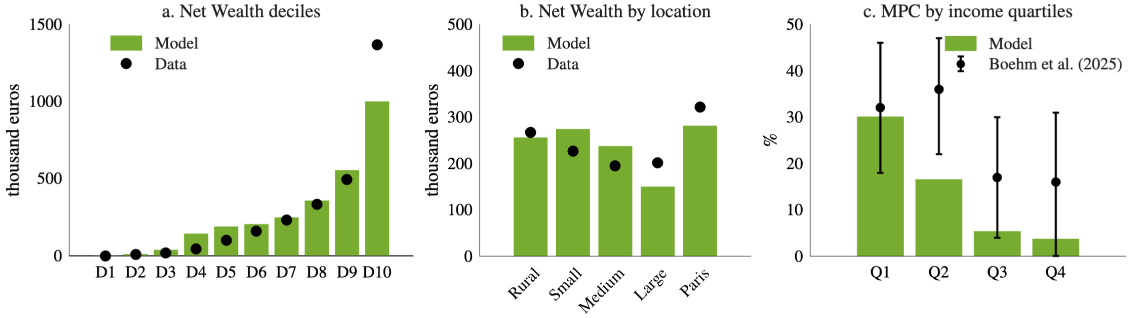
Notes. a: migration cost from k to k' in the model, as % of income. *b* and *c*: change in model probability of migrating in region k', following a decrease in average labor income tax rate in rural areas, see text.

The second approach to disciplining migration costs is to estimate the dynamic response of migration probabilities following changes in tax rates, typically for high-income households. For example, Young and Varner (2011) finds that a change in the top income tax rate leads to a 0.1 percentage point change in the migration probability of millionaires. Similarly, Akcigit, Baslandze and Stantcheva (2016) estimates an elasticity of around 0.03 for local inventors. In contrast, Martinez (2017) finds much higher elasticities, ranging from 3.2 to 6.5, for wealthy Swiss taxpayers. In Spain, Agrawal and Foremny (2019) shows that a 1% increase in a region's net-of-tax rate relative to others increases the probability of moving to that region by 1.7 percentage points. In panels *b* and *c* of Figure 6, we replicate this type of experiment in partial equilibrium. Specifically, we increase λ, the average net-of-tax rate on labor income, by 1% in the rural region. We then compute households' optimal location decisions, holding all other prices constant, and compare the resulting transition matrix to the baseline. For each income quintile, we examine the probability of migrating to region k', conditional on starting in another region. As expected, we observe positive values in the first column and negative values in the others: following the tax cut, households are more likely to move away from the rural region and more likely to stay elsewhere. Moreover, the change in migration probability is larger for low-income households than for higher-income ones. This is because wealthier individuals face higher effective migration barriers due to owning their houses. In Figure 6 panel *c*, we can see that it is mostly renters that are able to move away from rural areas, while homeowners are more likely to stay. In summary, tax changes can induce migration, particularly among renters with the ability to pay migration costs. We discuss this mechanism in our section 4, when analyzing the effects of carbon taxation a national policy whose impacts differ by location.

C.4 Other untargeted moments

In Figure 13, we present untargeted moments of our model. Our model does not match the upper tail of the wealth distribution but performs well in matching the distribution of wealth across the first wealth deciles (D1 to D9). Data for panel *a* comes from the 2021 *Histoire de vie et Patrimoine* survey. In panel *b* we compare average net wealth by location with data from the 2018 HVP (last available survey). This data was not available in the 2021 sample. We also report the MPC distribution in panel *c* and find that it falls within the lower bounds of Boehm, Fize and Jaravel (2025) using bank data in France.

Figure 13: Wealth inequalities and MPC heterogeneity

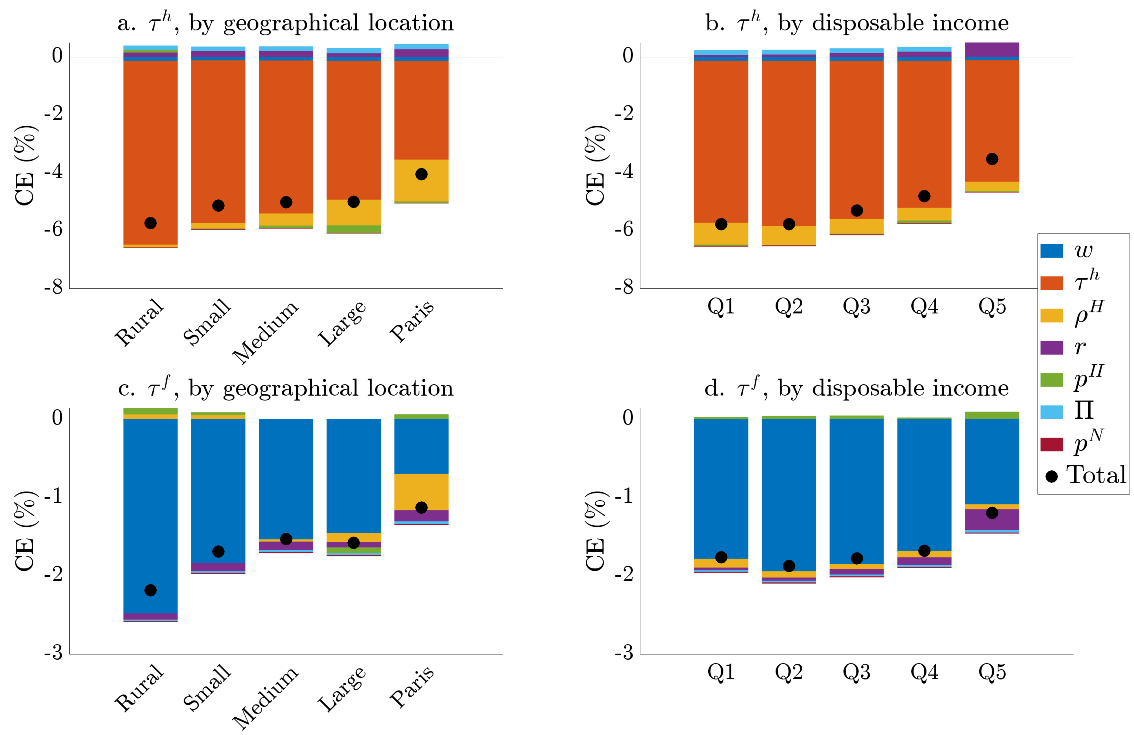


D Additional results – Section 4

D.1 Decomposition of welfare change

In Figure 14, we decompose the welfare effect of τ^h and τ^f into the 7 variables that affect directly households' budget constraint: wages (w), household carbon tax (τ^h), renting price (ρ^H), interest rate (r), housing price (p^H), profits (Π) and electricity price (p^N). To obtain this decomposition, we start from the transition path, and we shut one variable at a time by setting its value to the initial steady state level. The effect we attribute to each variable is the difference between the total effect (with all variables moving along the transition) and the partial transition (with all variables moving, except one).

Figure 14: Decomposition of the welfare effect

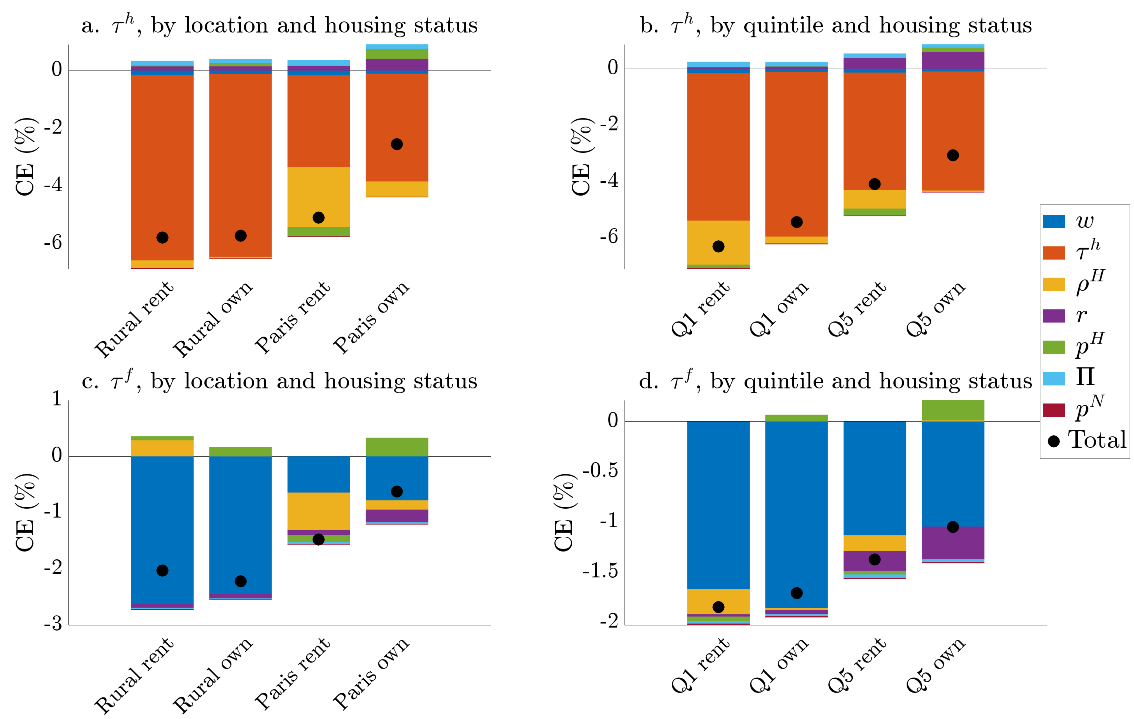


Notes. Decomposition of the welfare change (in % CE), through variables affecting households.

In euros, the additional annual carbon tax paid by each household in the new steady state after an increase in τ^h is equal to €1,082, 915, 818, 541, and 442 in rural, small, medium, large, and Paris, respectively. This corresponds to income shares of 5.0, 3.8, 3.3, 2.6, and 1.1%, respectively. Along the income dimension, households in quintiles Q1 to Q5 pay €627, 720, 800, 863, and 943, respectively, which correspond to income shares of 4.8, 4.3, 3.9, 3.4, and 1.7%, respectively.

In Figure 15, we provide the same decomposition, but separating renters and buyers, for rural versus Paris, Q1 versus Q5, and τ^h versus τ^f.

Figure 15: Decomposition by housing status

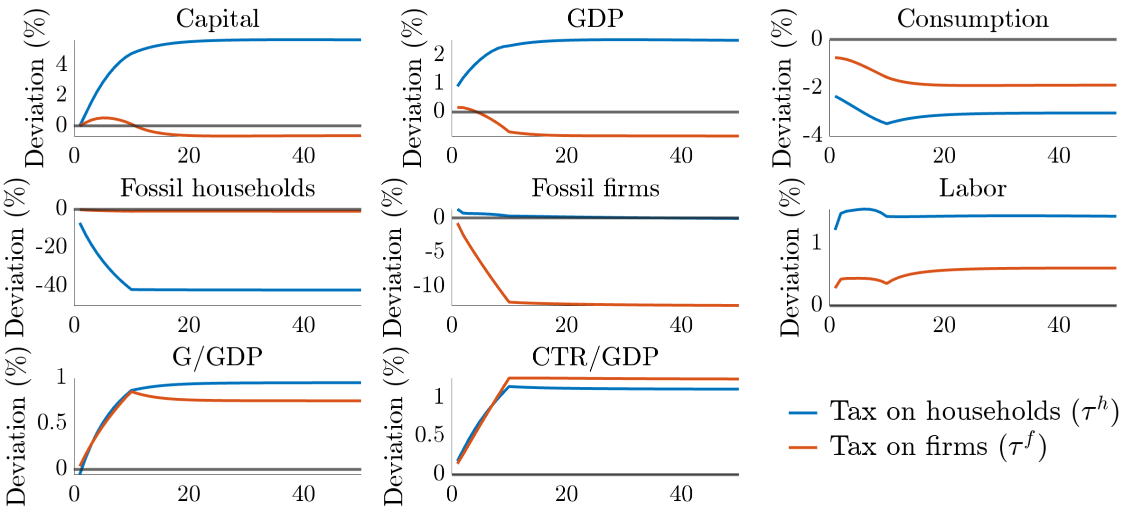


Notes. Decomposition of the welfare change (in % CE), through variables affecting households.

D.2 Impulse response functions

Below, we show the changes in aggregate and region-specific variables during the transition following increases in τ^h and τ^f. At the aggregate level, variables quickly converge to the new steady state and are essentially constant 20 years after the start of the transition, or 10 years after the final carbon tax increase. Fossil fuel consumption by households and firms is unaffected by an increase in the carbon tax applied to firms and households, respectively. GDP rises under τ^h, as households compensate for the higher carbon tax by supplying more labor and increasing savings, whereas it falls under τ^f, as firms' optimal input allocation is distorted. However, these GDP changes do not align with welfare outcomes: the welfare cost is higher under τ^h than under τ^f. Finally, household consumption declines in both scenarios: under τ^h because of higher taxes and distortions in their consumption basket, and under τ^f because of lower income, particularly wages.

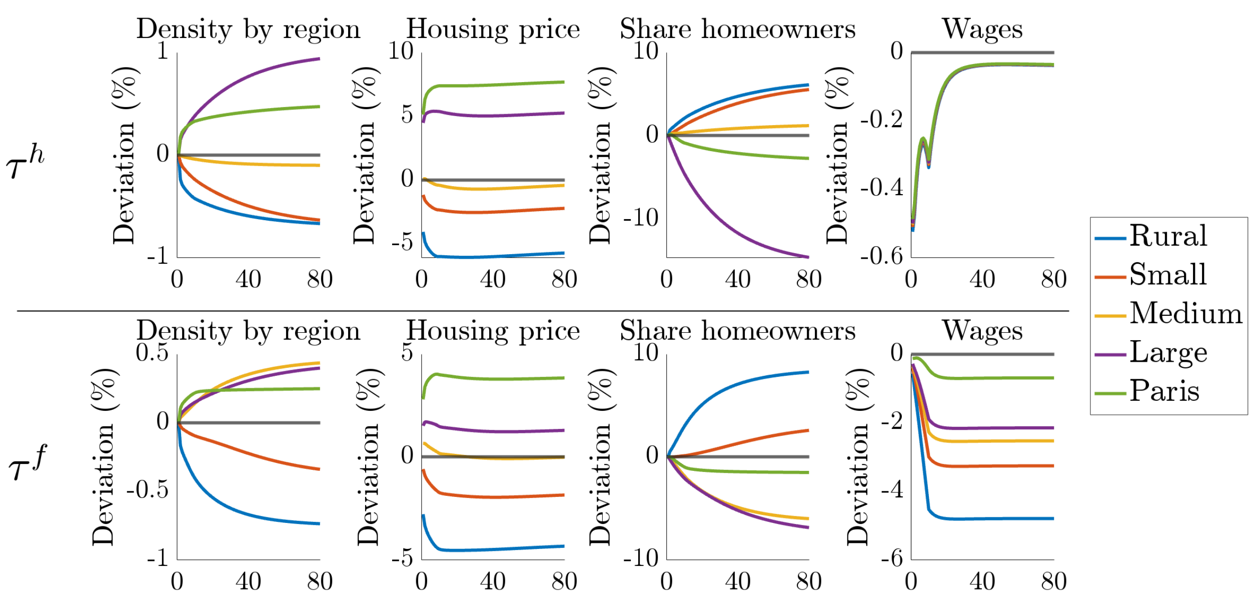
Figure 16: Change in aggregate variables compared to initial steady state



Notes. Variables are expressed in deviation compared to initial steady state, for the τ^h transition (in blue) and the τ^f transition (in red).

The paths of region-specific variables are qualitatively similar under τ^h and τ^f. Both transitions reduce the population in rural areas and small cities, while increasing it in large cities and in Paris. These changes are directly reflected in housing prices and, consequently, in the share of homeowners. Wages decrease slightly in each region under τ^h due to the increase in labor supply. The decline in wages is much larger, and more unequal across regions, under τ^f, as firms in rural areas are heavily penalized by the carbon tax.

Figure 17: Change in regional variables compared to initial steady state



Notes. Variables are expressed in deviation compared to initial steady state, for the τ^h transition (top panels) and the τ^f transition (bottom panels).

D.3 Policy implications of EU ETS 1 and EU ETS 2

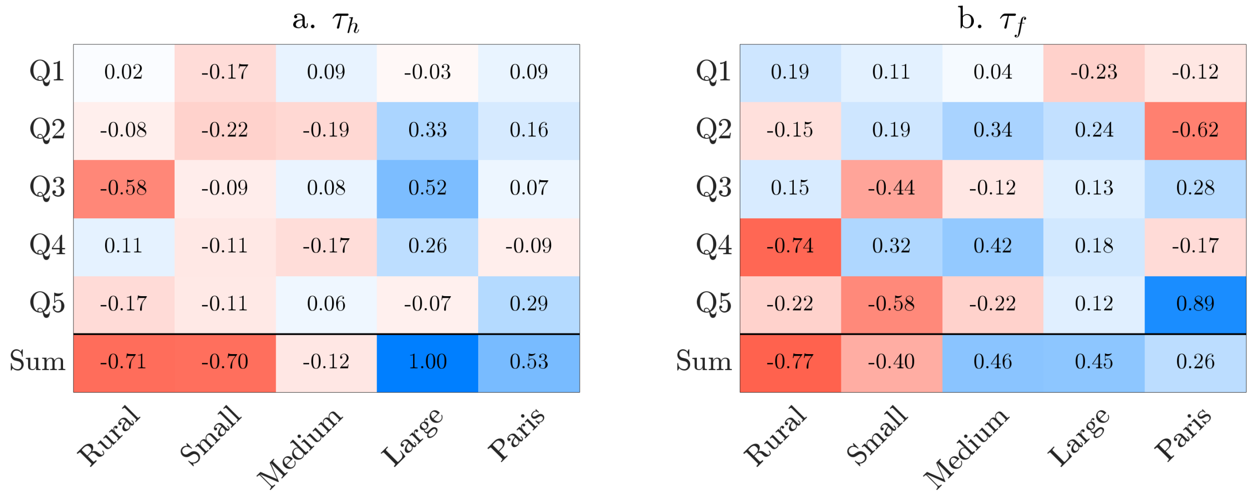
Although carbon taxes and carbon quotas are different, our framework can give us insights into the expected effects of the European Union Emissions Trading System (EU ETS). The first scheme (EU ETS 1), introduced in 2005 and targeting specific industrial sectors, is similar to our tax on firms, denoted as τ^f. In contrast, the upcoming extension (EU ETS 2, also known as Phase 4), scheduled for 2027 and covering sectors not included in the initial phase – primarily goods directly consumed by households – is more analogous to our tax on households, τ^h. In Figure 7, we set τ^f or τ^h such that, at the final steady state, total emissions are reduced by 10% compared to the initial steady state. This represents a carbon tax increase by €62 per ton of CO_2eq for firms, and by €385 for households. As firms emit more and exhibit greater elasticity of substitution for clean energy, they require lower taxes to reduce emissions by the same amount. At the peak of the EU ETS 1 in 2023, the price of a ton of CO_2 reached €100, which translates into a 16% decrease in total emissions in our model, assuming EU ETS 1 covers all direct emissions by firms. For the future EU ETS 2, the first three years will include a price containment mechanism, whereby if the price exceeds €45, additional allowances may be released. According to our simulations, this maximal price translates into a 1.2% decrease in total emissions, provided the EU ETS 2 extension covers all direct household emissions. Going forward, assuming a future price of €100 for both the current EU ETS and its extension, and assuming they cover all direct emissions from both firms and households, our model predicts a decline of 19% in total emissions, and a welfare cost equal to -4.3% CE, or €900 per year.

D.4 Migration and Welfare

D.4.1 Density change

Figure 18 shows, for each group area $\times$ income quintile, the change in population between the initial and final steady states. The sum of each line is equal to 0, as the share of households in each quintile is always 20%, and the sum of each column is different from 0, as households migrate between regions.

Figure 18: Density change by income and region between steady states

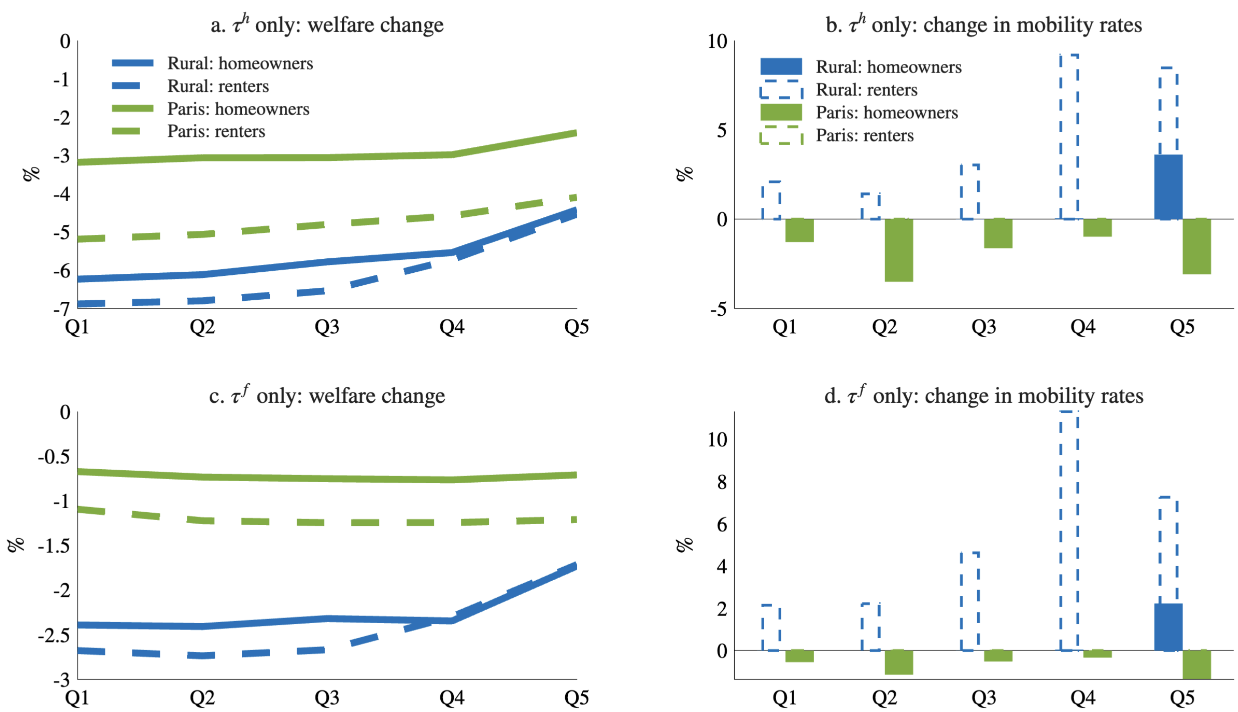


Notes: change in density in each sub-group between the initial and final steady state, after an increase in τ^h (panel a) and τ^f (panel b).

For both taxes, households migrate from rural areas and small cities to large cities and Paris. Under τ^h, migration is concentrated in the middle of the distribution: most of the density change comes from households in Q3. Under τ^f, poorer households tend to leave Paris, while richer households tend to leave rural areas.

D.4.2 Higher monetary migration costs

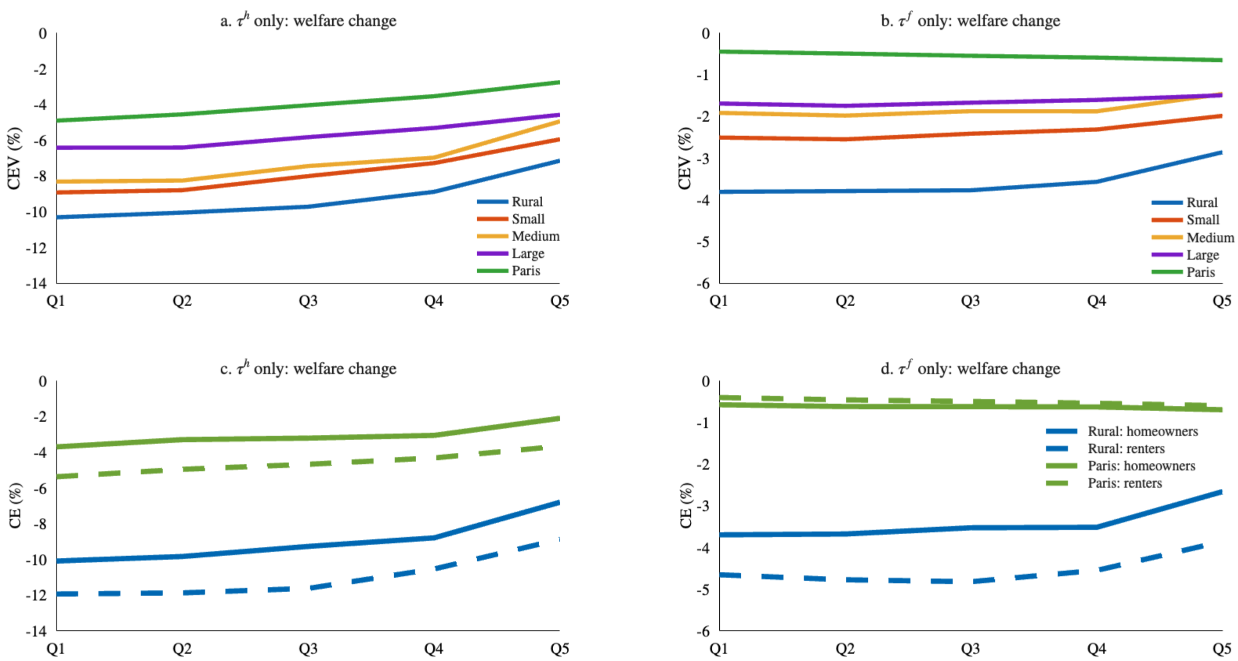
Figure 19: Welfare and change in mobility by income, location and housing status. Model with 50% higher migration costs.



Notes. In panel *a* and *c*, changes in welfare for τ^h and τ^f, for rural (blue) and Parisian households (green), separating homeowners (solid line) and renters (dashed line). In panel *b* and *d*, changes in probability of leaving the area for τ^h and τ^f, for rural (blue bar) and Parisian households (green bar), separating homeowners (solid bar) and renters (dashed bar).

D.4.3 No migration

Figure 20: Average welfare effect by location, income and housing status. Model with no migration.



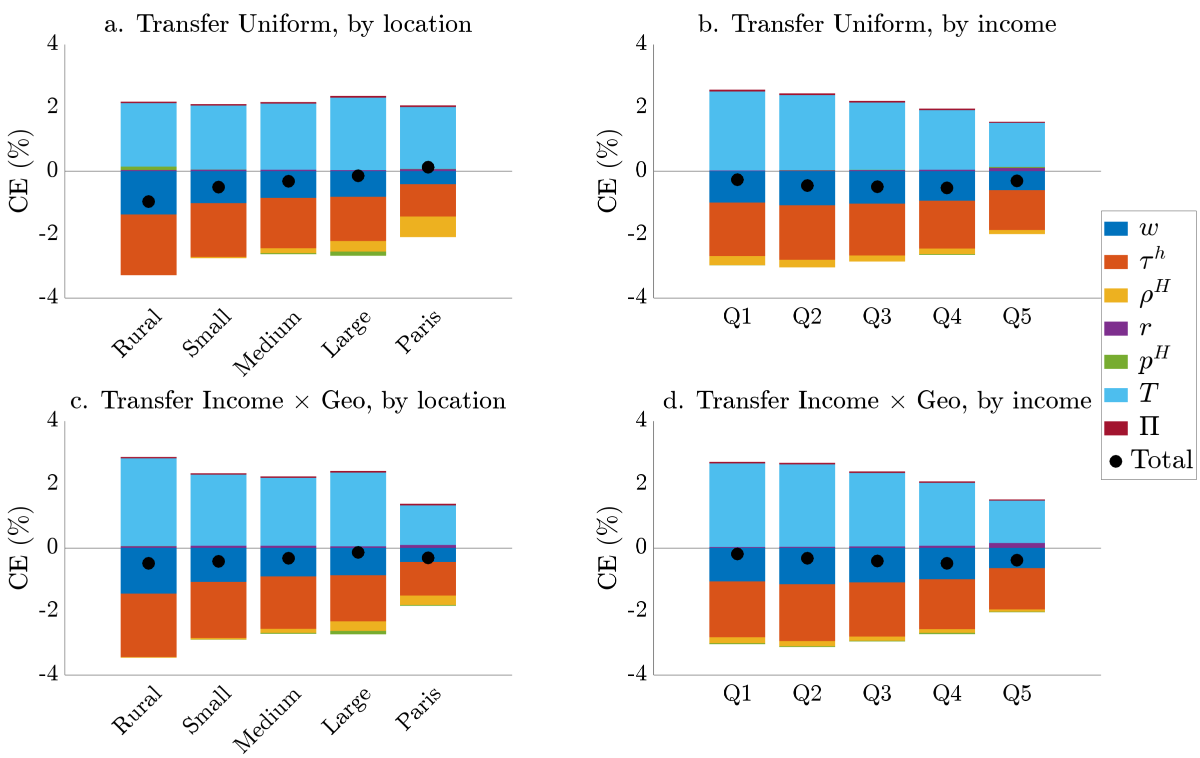
Notes. In panels *a* and *b*, average welfare change between the first period of the transition and the initial steady state for τ^h and τ^f. In panels *c* and *d*, changes in welfare, for rural (blue) and Parisian households (green), separating homeowners (solid line) and renters (dashed line).

E Additional results – Section 5

E.1 Recycling policies: additional results

In Figure 21, we decompose the welfare effect of our "Uniform" and "Income × Geography" transfers into the 7 variables that affect directly households' budget constraint: wages (w), household carbon tax (τ^h), renting price (ρ^H), interest rate (r), housing price (p^H), transfers (T) and profits (Π).

Figure 21: Decomposition of the welfare effect for scenarios 2 and 4



Notes. Decomposition of the welfare change (in % CE), through variables affecting households, in scenario 2 with uniform transfers (panels *a* and *b*) and scenario 4 with income and location-specific transfers (panels *c* and *d*).

In euros, the additional transfer received by each household in the new steady state with "Uniform" transfers is €432. With the "Income × Geography" transfer, the additional transfers are €652, 479, 431, 446, and 209 for rural, small, medium, large, and Paris households, respectively (corresponding to 3.0, 2.0, 1.8, 2.2, and 0.5% of their income). Along the income dimension, households in quintiles Q1 to Q5 receive transfers of €495, 500, 485, 456, and 341, respectively (corresponding to 3.8, 3.0, 2.4, 1.8, and 0.6% of income).

Finally, we can also compute the net transfers (what households receive as transfer minus what they pay as carbon tax). We restrict the analysis on τ^h, which is directly paid by households, and rescale transfers accordingly. In the "Uniform" transfer scenario, we obtain net transfers of €−90, −32, +7, +70, and +93 for rural, small, medium, large, and Paris households, respectively. This implies that carbon tax with uniform rebating redistributes from rural to Parisian households. With the "Income × Geography" transfer, the net transfers are €−8, −20, −3, +68, and −10, respectively, reducing the maximal loss.[14] Note that by construction, these partial-equilibrium gains and losses sum to zero when weighted, but they are not a direct measure of welfare or distributive effects, as they ignore general equilibrium effects. Due to the distortive nature of carbon taxes, taxing one euro and redistributing it to households reduces overall welfare, as illustrated in Table 1.

E.2 Migration & Transfers

In Figure 22, we show the density change between steady states, for each transfer rule. Migrations are largely similar for the first 3 scenarios, as they do not equalize the carbon tax burden between locations, pushing rural households to migrate towards large cities. However, the last scenario reduces density change between regions, with less households leaving rural areas and less households joining Paris.

[14] Along the income dimension, net transfers for Q1 to Q5 are €+29, +19, −18, −9, and −21, respectively, for the "Uniform" transfer scenario, and €+119, +31, −15, −10, and −124, respectively, for the "Income × Geography" transfer.

Figure 22: Density change for different rebating policies

a. Benchmark G

	Rural	Small	Medium	Large	Paris
Q1	0.04	0.05	0.08	-0.14	-0.02
Q2	-0.08	-0.17	0.10	0.25	-0.10
Q3	0.03	-0.14	-0.07	0.18	-0.00
Q4	-0.46	0.08	0.22	0.26	-0.10
Q5	-0.22	-0.29	-0.10	0.05	0.56
Sum	-0.69	-0.46	0.22	0.59	0.34

b. Uniform

	Rural	Small	Medium	Large	Paris
Q1	0.05	0.05	0.08	-0.14	-0.04
Q2	-0.18	-0.22	0.14	0.23	0.04
Q3	0.09	-0.10	-0.03	0.17	-0.13
Q4	-0.44	0.06	0.13	0.31	-0.06
Q5	-0.17	-0.22	-0.09	-0.04	0.52
Sum	-0.65	-0.43	0.24	0.53	0.32

c. Income

	Rural	Small	Medium	Large	Paris
Q1	0.06	0.03	0.07	-0.12	-0.04
Q2	-0.18	-0.20	0.22	0.24	-0.08
Q3	0.00	-0.09	-0.07	0.17	-0.02
Q4	-0.42	0.06	0.18	0.24	-0.05
Q5	-0.14	-0.26	-0.12	0.02	0.50
Sum	-0.68	-0.47	0.29	0.55	0.31

d. Income $\times$ Geography

	Rural	Small	Medium	Large	Paris
Q1	0.05	0.01	0.12	-0.10	-0.09
Q2	-0.13	-0.10	0.09	0.22	-0.08
Q3	0.01	-0.09	0.02	0.13	-0.07
Q4	-0.25	0.05	0.01	0.26	-0.07
Q5	-0.06	-0.19	-0.09	-0.03	0.37
Sum	-0.37	-0.31	0.15	0.48	0.06

Notes. Density change by income and region between steady states, for carbon tax revenue used to increase G (panel *a*), uniform T (panel *b*), income-dependent T (panel *c*), or income and geography T (panel *d*).

F Robustness – Section 6

In this section, we compute the distributive effects of carbon taxes by location and income, for alternative values of our key parameters. Moreover, we also consider the cases where fossil fuel emissions and public in-kind benefits G enter the utility function. We consider the following scenarios: (1) $\sigma = 0.4$ (against 0.2 in the benchmark model), (2) $\epsilon_h = 1.3$ (against 1.5), (3) $\sigma_y = 0.2$ (against 0.05), (4) $\epsilon_y = 1.3$ (against 1.5), (5) $\delta_H = 0.3$ (against 0.2), (6) $\delta_F = 0.2$ (against 0), (7) emissions enter the utility through a damage function (against no value), and (8) in-kind benefits enter the utility (against no value).

For each specification, we reproduce the "Benchmark G" scenario: we recalibrate carbon taxes such that emissions fall by 10%, and compute the transitional dynamics between the two steady states. We present our results in Table 14.

Table 14: Average welfare change by location and income, different elasticities

	Scenario	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**All**	**Δ Rural–Paris**
	Benchmark	−3.13	−2.67	−2.54	−2.56	−2.00	−2.61	−1.13
(1)	$\sigma = 0.4$	−2.96	−2.53	−2.40	−2.41	−1.91	−2.48	−1.05
(2)	$\epsilon_h = 1.3$	−3.74	−3.22	−3.07	−3.09	−2.44	−3.15	−1.30
(3)	$\sigma_y = 0.2$	−2.79	−2.36	−2.21	−2.22	−1.73	−2.30	−1.06
(4)	$\epsilon_y = 1.3$	−3.57	−3.03	−2.88	−2.90	−2.26	−2.97	−1.31
(5)	$\delta_H = 0.3$	−3.15	−2.65	−2.48	−2.44	−1.88	−2.56	−1.27
(6)	$\delta_F = 0.2$	−3.16	−2.70	−2.57	−2.59	−2.02	−2.64	−1.14
(7)	Emissions in U	−2.26	−1.79	−1.66	−1.65	−1.09	−1.73	−1.17
(8)	G in U	−1.60	−1.12	−0.98	−0.96	−0.40	−1.05	−1.20
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**	**Δ Q1–Q5**
	Benchmark	−2.91	−2.97	−2.77	−2.55	−1.87	−2.61	−1.04
(1)	$\sigma = 0.4$	−2.73	−2.79	−2.61	−2.43	−1.82	−2.48	−0.91
(2)	$\epsilon_h = 1.3$	−3.48	−3.56	−3.32	−3.08	−2.32	−3.15	−1.16
(3)	$\sigma_y = 0.2$	−2.54	−2.61	−2.43	−2.26	−1.68	−2.30	−0.86
(4)	$\epsilon_y = 1.3$	−3.29	−3.36	−3.14	−2.9	−2.15	−2.97	−1.14
(5)	$\delta_H = 0.3$	−2.82	−2.91	−2.71	−2.53	−1.83	−2.56	−1.00
(6)	$\delta_F = 0.2$	−2.94	−3.01	−2.80	−2.58	−1.89	−2.64	−1.05
(7)	Emissions in U	−2.02	−2.09	−1.88	−1.66	−0.98	−1.73	−1.04
(8)	G in U	−1.34	−1.42	−1.21	0.99	−0.31	−1.05	−1.03

Notes. Average welfare change between the first period of the transition and the initial steady state, expressed in consumption-equivalent terms. For each parameters, we recalibrate final carbon taxes such that all scenarios have a 10% reduction in total emissions.

(1) Elasticity of substitution between G&S consumption and energy ($\sigma = 0.4$). Increas-

ing σ reduces welfare losses across all groups. For example, rural welfare losses decline to -2.96% CE (compared with -3.13% CE in the benchmark), and losses for the Q1 group fall to -2.73% CE (compared with -2.91% CE). This reflects households' greater ability to substitute away from fossil fuels when prices increase. A higher elasticity also mitigates inequality in welfare impacts, both across locations and across income groups. The rural-Paris welfare gap – defined as the difference between the average welfare loss in rural areas and the average welfare loss in Paris (in consumption-equivalent terms) – decreases from -1.13% CE in the benchmark to -1.05% CE. Similarly, the Q1–Q5 gap declines from -1.04% CE to -0.91% CE.

(2) Elasticity of substitution between fossil fuels and electricity for households ($\epsilon_h = 1.3$). Reducing ϵ_h from 1.5 to 1.3 increases welfare losses across all groups, as it becomes more difficult to substitute for households. Rural losses rise to -3.74% CE and Q1 losses increase to -3.48%. The rural-to-Paris welfare gap widens to -1.30% CE, and the Q1-to-Q5 gap increases to -1.16% CE.

(3) Elasticity of substitution between capital-labor and energy for firms ($\sigma_y = 0.2$). With a higher σ_y, welfare costs are smaller for rural (-2.79% CE) and poor (-2.54% CE) households. The rural-to-Paris welfare gap decreases to -1.06% CE, and the Q1-to-Q5 gap narrows to 0.86%. This indicates that greater substitution flexibility in production not only lowers overall welfare costs but also reduces income and geographic disparities.

(4) Elasticity of substitution between fossil fuels and electricity for firms ($\epsilon_y = 1.3$). Decreasing ϵ_y from 1.5 to 1.3 reduces firms' ability to substitute away from fossil fuels, thereby requiring a higher carbon tax to achieve a 10% emissions reduction. As a result, wages decline in rural areas and spatial inequality increases markedly: the rural–Paris welfare gap widens to -1.31% CE (from -1.13%). The Q1-to-Q5 gap also increases, as wages are the primary source of income for low-income households.

(5) Elasticity of housing supply ($\delta_H = 0.3$). Increasing δ_H slightly reduces aggregate losses relative to the benchmark, by 0.03% CE, but it has sizeable distributive effects. The rural–Paris welfare gap widens to -1.27% CE (from -1.13%). As households move from rural areas to Paris, housing prices in rural areas fall, which mitigates the losses of those who remain. However, when housing supply is more elastic, it adjusts more strongly to the price decline, limiting the drop in housing prices and thereby worsening outcomes for rural households who stay.

(6) Endogenous fossil fuel price ($\delta_F = 0.2$). We depart from our assumption of a fixed fossil fuel price ($\delta_F = 0$) and instead allow the price to respond to changes in domestic fossil fuel demand, with an elasticity $\delta_F = 0.2$. At the new steady state, fossil price falls by 2.1% due to the 10% decline in fossil demand, but this decline is compensated by a higher carbon

tax necessary to reduce emissions. The overall effect is very similar to the benchmark, with a decrease by 0.03 CE for every group.

(7) Valuing emissions. Temperature dynamics follow Dietz and Venmans (2019), in which global mean temperature change relative to pre-industrial levels, T_t, evolves according to $T_{t+1} = T_t + \upsilon\,(\xi \mathcal{E}_t - T_t)$ where $\xi = 0.00048°\mathrm{C}/\mathrm{GtCO}_2$ denotes the transient climate response to cumulative emissions and $\upsilon = 0.5$ governs temperature adjustment. Cumulative global emissions evolve according to $\mathcal{E}_{t+1} = \mathcal{E}_t + F_t^{\mathrm{RoW}} + F_t$ with F_t and F_t^{RoW} denoting net emissions in France and the Rest of the World. Initial conditions are $\mathcal{E}_0 = 2605$ GtCO_2 taken from Friedlingstein et al. (2024) and $T_0 = 1°\mathrm{C}$ as in Bilal and Känzig (2026).

(8) Valuing G. As the carbon tax revenue increases G, and as G is valued equally between each households, carbon taxes have the same distributive effects as in the benchmark, but shifted upwards by +1.56% CE.

References – Appendix

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