Geography versus Income: The Heterogeneous Effects of Carbon Taxation

Charles Labrousse* and Yann Perdereau†

August 18, 2025

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 are employed in firms that emit 2.7 times more greenhouse gases. We incorporate these insights into a spatial heterogeneous-agent model with endogenous migration and wealth accumulation, linking spatial and macroeconomic approaches. After an increase in carbon taxes, we quantify that rural households face 20% higher welfare losses than urban households. In an optimal revenue-recycling exercise, we compare transfers targeting income and geography, and show that neglecting for geography reduces welfare gains by 7%. We conclude 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.

We are deeply grateful to Axelle Ferriere and Katheline Schubert for their help since the beginning of this project. We also thank for their precious advice: Barbara Annicchiarico, Adrien Auclert, Tobias Broer, Mireille Chiroleu-Assouline, Thomas Douenne, Eustache Elina, Adrien Fabre, Mouez Fodha, Stephie Fried, Raphaël Lafrogne-Joussier, François Langot, Julien Matheron, Martí Mestieri, Gilbert Metcalf, Mar Reguant, Fabien Tripier, and participants at conferences and seminars for their helpful comments.

*Insee/Paris School of Economics, charles.labrousse@psemail.eu

†Paris School of Economics, yann.perdereau@psemail.eu

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 energy consumption 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 choose whether to migrate in response to carbon taxation, accounting for mobility frictions and relocation incentives. The interaction between savings and migration costs enables agents to accumulate resources to migrate and smooth the adverse effects of the carbon tax, while borrowing constraints impede mobility and give rise to "trapped" households. These dynamic features also allow us to evaluate the welfare costs over time, reflecting a gradual process of household reallocation. Our model successfully replicates the observed heterogeneity in income, wealth, 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. Under a welfare-maximizing planner with an emissions constraint, we evaluate a range of revenue-recycling scenarios, from increased public spending to targeted transfers based on location and income. Our paper yields three key findings.

First, using micro data on households and firms, we show that **geography is more important than income in explaining 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 time horizons. In our benchmark policy scenario, targeting a 10% reduction in emissions, median welfare losses in rural areas are 20% higher than those in Paris: -17.3% versus -14.5%, measured as a welfare-equivalent reduction in wealth relative to initial income. We decompose these effects by distinguishing between taxes on households' direct emissions and those on firms' direct emissions. The household tax is highly regressive, as fossil fuels are necessities, disproportionately burdening low-income households. In contrast, the firm tax is less regressive: it primarily reduces wages, which adversely affect middle-income households, and lowers interest rates, thereby harming wealthier households. Moreover, these taxes trigger distinct migration patterns: while the household tax drives low-income households out of rural areas to escape steep energy costs, the firm tax pushes high-income households out due to falling wages. Our findings underscore that the welfare costs of carbon taxation evolve over time, with migration playing a crucial role in mitigating its impact across regions. We also discuss the implications of our results for the two European carbon emissions trading systems: EU-ETS 1 and EU-ETS 2.

Third, we find that **ignoring geographical location in recycling rules reduces welfare gains by 7%**. Our optimal transfer-recycling policy, which targets both income and location, outperforms income-only targeting by 7.3% and uniform transfers by 38%. This approach not only boosts median welfare across all income and geographic groups but also reduces the share of households experiencing welfare losses by 10% compared to income-only transfers. This is because tailoring transfer progressivity to each city's income distribution enhances the effectiveness of transfers in compensating for local carbon-tax burdens. As a result, location-based targeting reduces migration flows and the associated relocation costs. These results are robust across alternative welfare objectives, Pareto weights, and parametric formulas.

Our main contribution is to develop a unified framework for analyzing the general equilibrium distributive effects of carbon taxation by jointly examining its impact on both households and firms, incorporating both income and spatial heterogeneity. This framework bridges two key strands of the literature: the distributive effects of carbon taxation, and the modeling of income and geographical heterogeneity among households.

The literature on the *distributive effects of carbon taxation* examines the heterogeneous fiscal incidence of carbon taxes across households, using micro-simulation, Computable General Equilibrium (CGE), or heterogeneous-agent general equilibrium models. The general approach is to link the household income distribution to changes in energy prices, which are impacted by carbon taxes. This requires accounting for both the direct effect (households consume fossil fuels for housing and transportation) and the indirect effect (firms use energy as an input, which affects the prices of other inputs, such as capital and labor, thus influencing income distribution). Based on micro-simulations, Cronin, Fullerton and Sexton (2019) for the U.S. and Douenne (2020) in the French context conclude that carbon taxes are regressive, with most of the heterogeneity occurring within income quantiles. We confirm that carbon taxes are regressive and explicitly model this *within-quantile* heterogeneity by introducing geographical differences, which are a key determinant of tax burden disparities across households. Within the CGE literature, Rausch, Metcalf and Reilly (2011) and Goulder et al. (2019) conclude that the progressivity of *source-side* effects (related to changes in relative factor prices) offsets the regressive *use-side* effects (related to the composition of total expenditures). Compared to these studies, we endogenize income and wealth distributions by incorporating idiosyncratic income risk, and we introduce geographical heterogeneity. Our framework is similar to Känzig (2023), who integrates energy into both household final consumption and firm inputs; we add an additional layer of heterogeneity by considering the spatial dimension. Finally, a central component of this literature is the use of carbon tax revenue. As in Goulder et al. (2019) and Mathur and Morris (2014), we find that targeted transfers can improve welfare and mitigate regressivity. However, we show that income-based transfers alone are insufficient to compensate rural households, motivating the exploration of geography-based transfers. Unlike Fried, Novan and Peterman (2024) and Barrage (2020), who use revenues to reduce distortive taxes, we focus on direct transfers, as they explicitly separate carbon tax revenue from the general state budget, which may enhance the political acceptability of the policy.

This paper also contributes to the growing *quantitative macro-spatial literature* by integrating a spatial dimension into heterogeneous-agent general equilibrium models. Building on Aiyagari (1994) framework, we study the aggregate and distributional effects of energy shocks and climate policies, as in Auclert, Monnery, et al. (2023), Langot et al. (2023), Pieroni (2023), Chan, Diz and Kanngiesser (2024) and Bayer et al. (2025). We depart from these studies along several dimensions. First, motivated by the geographic heterogeneity in emissions from both households and firms, we introduce a spatial layer into the general equilibrium structure of heterogeneous-agent models. Our framework incorporates endogenous migration, region-specific energy needs, and segmented housing and labor markets. Second, we extend the standard consumption structure by introducing non-homothetic preferences, following Comin, Lashkari and Mestieri (2021), to better capture heterogeneous energy demand across households. On the production side, we include multiple sectors, as in Barrage (2020), to allow for heterogeneous energy use across firms. Third, we connect to the quantitative spatial literature on migration and worker reallocation in static or partial equilibrium settings (e.g., Desmet and Rossi-Hansberg (2014), Fajgelbaum et al. (2019) or Couture et al. (2024)) by embedding endogenous savings and mobility decisions. This addition allows us to study how borrowing constraints interact with migration costs to generate gradual spatial reallocation in response to carbon taxation. These frictions slow adjustment dynamics and enable the comparison of welfare and population changes across different time horizons. Finally, we contribute to an emerging literature that combines joint consumption-saving and location choices in quantitative models. Related studies have focused on different policy environments: Ferriere, Navarro, Reyes-Heroles, et al. (2018) analyzes trade shocks, Giannone et al. (2023) examines moving vouchers, and Greaney (2023) explores responses to local productivity shocks. In contrast, we study how carbon taxation affects household migration decisions. Our framework highlights how mobility frictions and local economic conditions interact with household wealth to produce gradual and uneven migration responses, with important implications for welfare, spatial inequality, and policy design.

The remainder of the paper is organized as follows. Section 1 presents descriptive evidence on the distribution of carbon emissions across households and firm. Section 2 introduces our quantitative model. Section 3 discusses the calibration of the model using French data. Section 4 presents our main results, while Section 5 examines optimal carbon taxes and rebate policies. Finally, Section 6 concludes.

1 Descriptive Evidence

This section presents descriptive evidence on the distribution of greenhouse gas emissions by households and firms in France. Our analysis reveals that geographic factors outweigh income differences. 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 heating 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. We then consider total energy consumption as the sum of fossil fuel expenditures and total electricity expenditures.[1] Throughout the paper, we classify locations into five city types: Rural, Small cities, Medium cities, Large cities, and Paris, based on population size.[2] These categories represent 23.5%, 26.0%, 18.5%, 13.4%, and 18.6% of the population, respectively. For a fair comparison, we also categorize households into five income groups, ranked by disposable income quintiles.

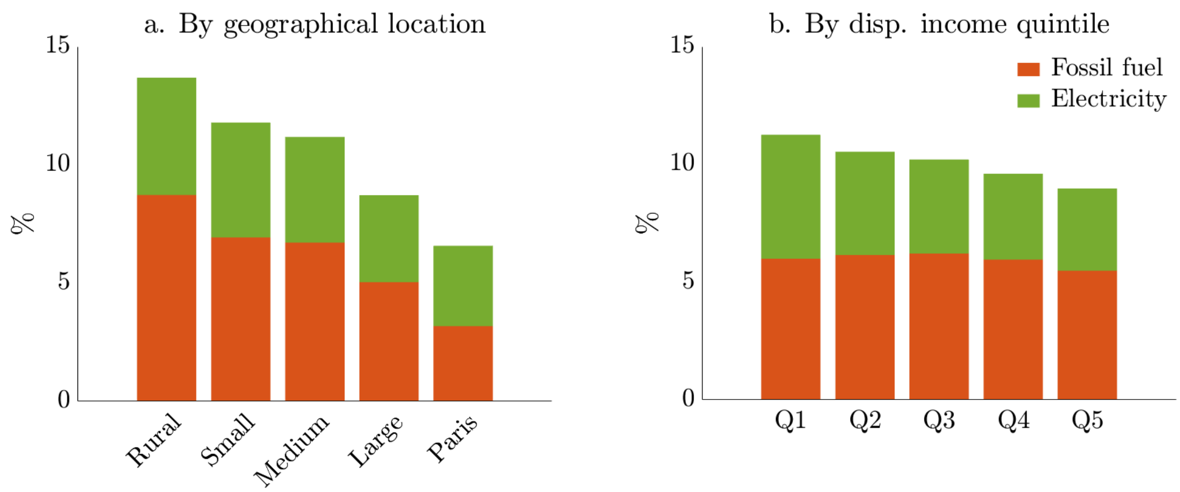
Empirical Results. We regress households' energy and fossil fuel expenditures on city type, income quintile, and control variables, as detailed in Appendix A.4. This approach helps control for potential correlation between income levels and location choices. The predicted shares of electricity and fossil 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

[1] 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.

[2] 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, we provide a map of France corresponding to these categories.

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.[3] 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: share of fossil fuel and electricity in total consumption expenditures, results net of controls (details in Appendix A.4). These are the mean energy share in each group (city type, income quintile) if the group had the same characteristics as the whole population.
Source: Authors' computations using Budget de Famille 2017

To explain these differences in energy shares, we break down household energy use into two categories: *housing* and *transportation*, as shown in Table 3 in Appendix.

Housing accounts for 5.2% of total expenditures on average (56% of energy consumption), but 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 administrative data[4] also reveal that rural households have nearly twice the living space of Parisian households — an average of 105.6 square meters compared to

[3] See Appendix A for details.
[4] Supplementary data is available in Appendix A.

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.

Transportation accounts 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. Consequently, geography is more important than income in explaining household energy shares, driven by higher housing and transportation costs in rural areas.

Table 1: 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.

The dominance of geography over income extends to many countries, as shown in Table 1. 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 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.

Therefore, **geography plays a more significant role than income in explaining the share of energy and fossil fuels in household expenditures**. Accounting for this geographic dimension is crucial for understanding the distributive effects of carbon taxation, as fossil fuels constitute the majority of households' direct emissions. However, carbon taxes affect not only households but also the firms that employ them.

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.[5] The BTS dataset has two advantages. First, it is exhaustive, containing 32 million workers per wave, providing rich demographic, geographic, and plant-level information. Second, it has a panel version that covers the entire work history of a representative set of workers (over 3 million individuals).[6] 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.[7] 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

[5] *Base Tous Salariés – fichiers Salariés.*

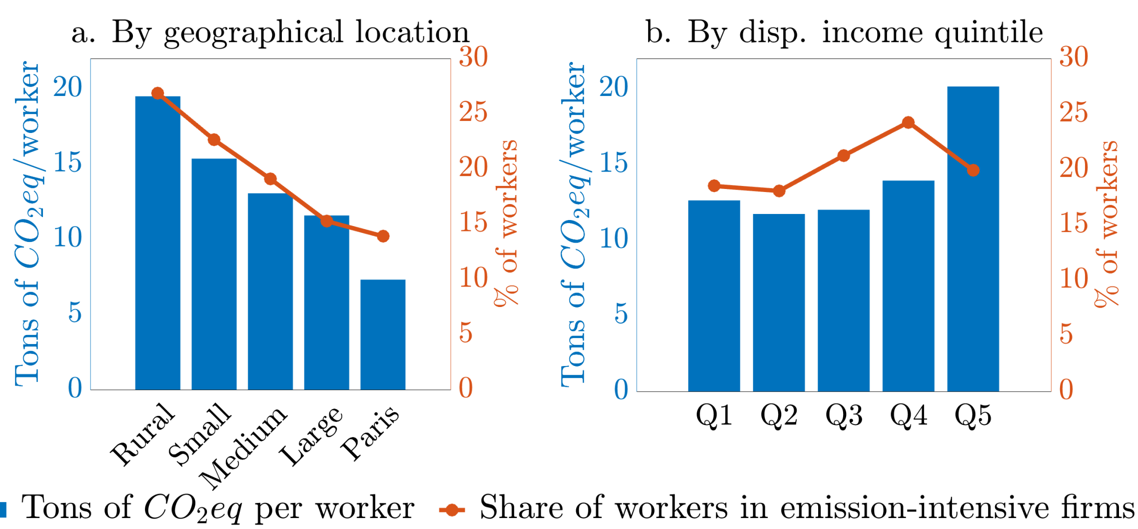
[6] We use the panel dimension of the dataset to analyze mobility rates across regions.

[7] See Appendix A.3 for details.

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.3 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.4. 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



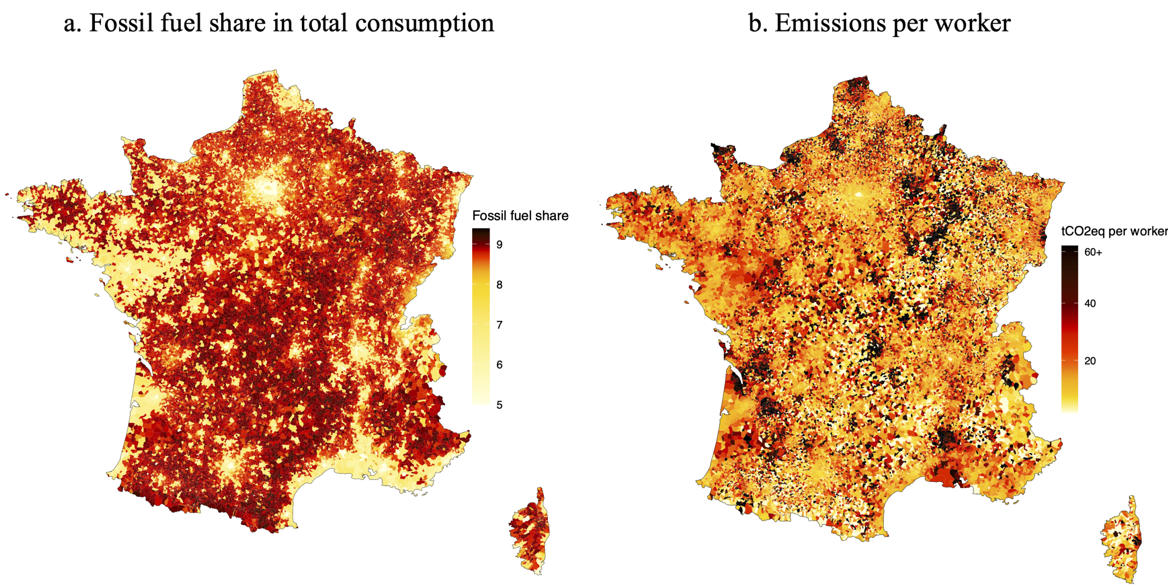
Notes: tons of $C0_2$eq imputed per worker, controlling for variables detailed in Appendix A.4. It represents the average tCO_2eq/worker in each group (city type, income quintile) if the group had the same characteristics as the whole population.

Source: Authors' computations using 2022 BTS-Salariés and National Accounts.

We provide a sectoral decomposition along the income and geography dimensions in Table 5 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 6 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



Sources: Panel *a*: BdF 2017 and 2021 households fiscal declarations. Panel *b*: 2022 BTS and national accounts

In conclusion, geography plays a more significant role than income in explaining both households' energy consumption 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 heterogeneous-agent à la Aiyagari (1994), with idiosyncratic productivity shocks leading to income and wealth heterogeneity, to spatial models, with segmented labor and housing markets, different subsistence energy levels by living areas, and endogenous migration choice. Our productive sector is composed of a regional final good producer in each living area, which uses capital, labor, electricity and imported fossil fuel as intermediate inputs. Another national representative firm produces electricity using capital and imported fuel. Finally, the fiscal authority has a complete set of instruments: a progressive labor income tax $\Gamma(\cdot)$, a flat capital income tax τ^k, a VAT tax τ^{VAT} and carbon taxes on households τ^h or firms τ^f. Carbon tax revenue is used either to increase public spending or to implement targeted transfers. Our algorithms, developed from scratch in MATLAB, are precisely detailed in Appendix B.

2.1 Households

The economy is populated by an infinite amount of households indexed by i that 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 $p^H(k)$, wage $w(k)$, and the mean and variance of the idiosyncratic productivity shock, so that the individual productivity is denoted $z_i(k)$. Households optimally choose the city type, taking into account a fixed migration cost: $\kappa(k, k') \geq 0$. 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, housing consumption H, asset a' at the beginning of next period, 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. Households supply an exogenous level of labor $\bar{l}$. Each household i of type k solves the following program[8] (omitting subscript i for clarity):

[8]Denoting a the assets at the beginning of the period, z the idiosyncratic productivity, and x' the next period of variable x, the Bellman equation is defined as $V(a,k,z) = \max_{u,a',k'} \left\{ \frac{u^{1-\theta}-1}{1-\theta} + \beta \mathbb{E}\left[V(a',k',z')|k,z\right] \right\}$, such that Equations (1) to (5) hold.

$$\max_{\{a_{t+1},k_{t+1},c_t,e_t^h,F_t^h,N_t^h\}_{t=0}^{+\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{u_t^{1-\theta}-1}{1-\theta} \right\}$$

subject to:

$$\Lambda_C^{\frac{1}{\sigma}} \left(\frac{c_t}{u_t^{\epsilon_C}} \right)^{\frac{\sigma-1}{\sigma}} + \Lambda_E^{\frac{1}{\sigma}} \left(\frac{e_t^h - \bar{e}(k_t)}{u_t^{\epsilon_E}} \right)^{\frac{\sigma-1}{\sigma}} + \Lambda_H^{\frac{1}{\sigma}} \left(\frac{H_t}{u_t^{\epsilon_H}} \right)^{\frac{\sigma-1}{\sigma}} = 1 \tag{1}$$

$$e^h = \left[(1-\gamma_h(k_t))^{\frac{1}{\epsilon_h}} (N^h)^{\frac{\epsilon_h-1}{\epsilon_h}} + \gamma_h(k_t)^{\frac{1}{\epsilon_h}} (F^h)^{\frac{\epsilon_h-1}{\epsilon_h}} \right]^{\frac{\epsilon_h}{\epsilon_h-1}} \tag{2}$$

$$\begin{aligned} &\underbrace{(1+\tau^{\text{VAT}}) \left[c_t + p_t^N N_t^h + (p_t^F + \tau_t^h) F_t^h \right] + p^H(k_t) H_t}_{\text{Total consumption expenditures}} + \underbrace{a_{t+1} - a_t}_{\text{Savings}} + \underbrace{\kappa(k, k')}_{\text{Migration cost}} \\ &\qquad = \underbrace{\Gamma\left(z_t(k_t) w(k_t) \bar{l} \right)}_{\text{Net labor income}} + \underbrace{(1-\tau^k) r_t a_t}_{\text{Net capital income}} + \underbrace{T_t(k_t, z_t, a_t)}_{\text{Transfers}} \end{aligned} \tag{3}$$

$$z_t(k_t) = e^{x_t(k_t)}\ ,\ x_t(k) = (1-\rho_z)\mu_z(k_t) + \rho_z x_{t-1}(k_t) + \epsilon_t,\ \epsilon_t \sim \mathcal{N}(0, \sigma_z(k_t)) \tag{4}$$

$$a_t \geq \underline{a} \tag{5}$$

Equation 1 implicitly defines utility 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_C, Λ_H and Λ_E control the share of expenditures devoted to c, H and e^h, and ϵ_C, ϵ_H and ϵ_E control the income elasticity of demand for each good. On top of this utility function, we 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...).

Equation 2 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 $\gamma_h(k)$.

Equation 3 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_t^F is subject to an excise carbon tax τ_t^h. On the revenue side, labor income is taxed according to a progressive tax rule $\Gamma(\cdot)$ defined later. Capital income is 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, or covering migration costs.

Equation 4 is the idiosyncratic productivity process. Productivity follows an AR(1) process with normally distributed shocks. We allow the mean μ_z and the variance σ_z to depend on the type k.

Finally, **Equation 5** 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:

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

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 industries are often located in rural areas, whereas less 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 (2023) 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 using capital k^N and fossil fuel F^N, according to the following program:

$$\max_{\{K_N,F_N,N\}} \Pi^N = p^N N - r^K K^N - (p^F + \tau^f)F^N$$

such that

$$N = (K^N)^\zeta (F^N)^{1-\zeta}$$

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 housing supply sector

Each city-type k has a housing supply $H^{\mathrm{S}}(k)$ that may react to the regional housing price:

$$H^{\mathrm{S}}(k) = H_k \left(p^H(k)\right)^{\delta_H}$$

where H_k is a constant and δ_H is the price elasticity of housing supply.

2.3 Fiscal authority

The fiscal authority gets revenue from taxes on labor income, capital income, consumption and carbon taxation (i.e. fossil fuel consumption). It uses its revenue to fund transfers (T), public spending (G) and public debt repayment ($r_t\bar{d}$). Denoting $\mu_t(a,z,k)$ the measure of households with state (a,z,k), the aggregation over all households is given by $X_t = \int x \ \mathrm{d}\mu_t(a,z,k)$ for $x \in \{a, c, F^h, N^h\}$, and firms aggregation $F_t^Y = \sum_k F_{k,t}^Y$. The government has the following budget constraint:

$$T_t + G_t + r_t\bar{d} = \int [z_t w_t l_t - \Gamma(z_t w_t l_t)] \,\mathrm{d}\mu_t + \tau^k r_t A_t + \tau^{\mathrm{VAT}} \left(C_t + p_t^N N_t^h + p_t^F F_t^h\right) \\ + \underbrace{\tau_t^h (1+\tau^{\mathrm{VAT}}) F_t^h + \tau_t^f (F_t^Y + F_t^N)}_{\text{Carbon tax revenue (CTR)}}$$

Following Heathcote, Storesletten and Violante (2017), we assume a progressive labor tax that gives the following net labor income:

$$\Gamma(zwl) = \lambda(zwl)^{1-\tau}$$

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 $\mu_t^{\bar{k}} = \mu_t(a,z,k=\bar{k})$ the regional aggregation of households of type $\bar{k}$. The firm aggregation is $X = \sum_k X(k)$ for $X \in \{K^Y, H^{\mathrm{S}}, Y, I^Y, F^Y, N^Y\}$. Finally, to close the model, we have the following market clearing conditions:

$$\begin{cases} A_t = K_t^Y + K_t^N + H_t^{\mathrm{S}} + \bar{d} & \text{(Asset)} \\ \forall k, \int zl \ \mathrm{d}\mu_t^k = L_k^Y & \text{(Labor)} \\ \forall k, \int H \ \mathrm{d}\mu_t^k = H_t^{\mathrm{S}}(k) & \text{(Housing)} \\ Y_t = C_t + I_t^N + I_t^Y + G_t + X_t + \int \kappa_t \mathrm{d}\mu_t & \text{(Goods and services)} \\ F_t = F_t^N + F_t^Y + F_t^h & \text{(Fossil fuel)} \\ N_t = N_t^Y + N_t^h & \text{(Electricity)} \end{cases}$$

Households' savings are claims on a mutual fund that holds capital, housing and public debt, and redistribute the average return to households according to the equation: $r_t a_t = (r_t^K - \delta)K_t + \sum_k p_{k,t}^H H_t^k + r_t d_t$. The goods and services (G&S) production (Y) is consumed by households (c), government (G) or foreigners (X), or invested by firms (I^N, I_k^Y), partly to compensate the depreciation rate, so that we have $I_t =$

$K_{t+1} - (1-\delta)K_t$. Electricity N is consumed as intermediate inputs by firms (N^Y), or as a commodity good by households (N^h).

We define the equilibrium as paths for households decisions $\{C_t, H_t, N_t^h, F_t^h, A_{t+1}, K_{t+1}\}_t$, G&S firm decisions $\{Y_{k,t}, L_{k,t}^Y, K_{k,t}^Y, F_{k,t}^Y, N_{k,t}^Y\}_{k,t}$, electricity firm decisions $\{N_t, K_t^N, F_t^N\}_t$, relative prices $\{r_t, w_{k,t}, p_t^N\}_{k,t}$, fiscal policies $\{\Gamma(.), \tau^k, \tau^{\text{VAT}}, \tau_t^h, \tau_t^f\}_t$, public expenditures $\{T_t, G_t\}_t$, and aggregate quantities, 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.

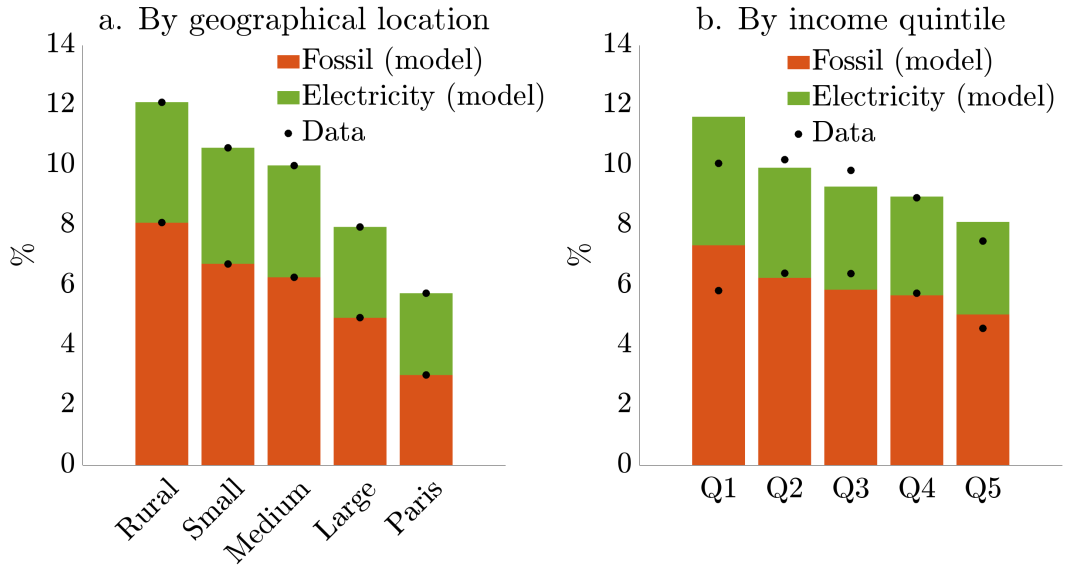
3 Calibration on French macro and micro data

As this paper assesses the distributive effects of carbon taxation, the main point of the calibration is to reproduce the energy mix used by households and firms in France, along the geography and income dimension. As shown in Section 1, households in rural areas consume more energy and fossil fuel than households in large cities, and work in more emission-intensive firms. We carefully calibrate the joint geography-income distribution, the migration patterns between regions, and the main aggregates. As explained in Appendix B, our calibration strategy is to directly integrate parameters as guesses of the model, so that each aggregate target is precisely matched. In this section, we describe how we choose the target for each parameter. The values for all parameters are presented in Table 8. Untargeted moments – income composition, taxes, wealth and MPCs distributions – are presented in Appendix C.

3.1 Households

Consumption heterogeneity. We use Λ_E and Λ_H to match the average energy and housing share in total expenditures, and we normalize Λ_C to 1 as in Comin, Lashkari and Mestieri (2021). The parameters ϵ_E and ϵ_H are calibrated to fit the non-homotheticity of energy and housing across the income distribution and ϵ_C is normalized to 1. We then add the $\bar{e}(k)$ to match the observed spatial heterogeneity in energy constraints. We normalize $\bar{e}(\text{Paris}) = 0$ and set the other $\bar{e}(k)$ to match the average energy share in each city type, 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: share of fossil fuel $[(p^F + \tau^h)F^h]$ and electricity $[p^N N^h]$ in total consumption expenditures $[c + (p^F + \tau^h)F^h + p^N N^h]$. Panel *a*: by geographical location. Panel *b*: by disposable income quintile, untargeted in the model.
Source: BdF 2017 Insee survey.

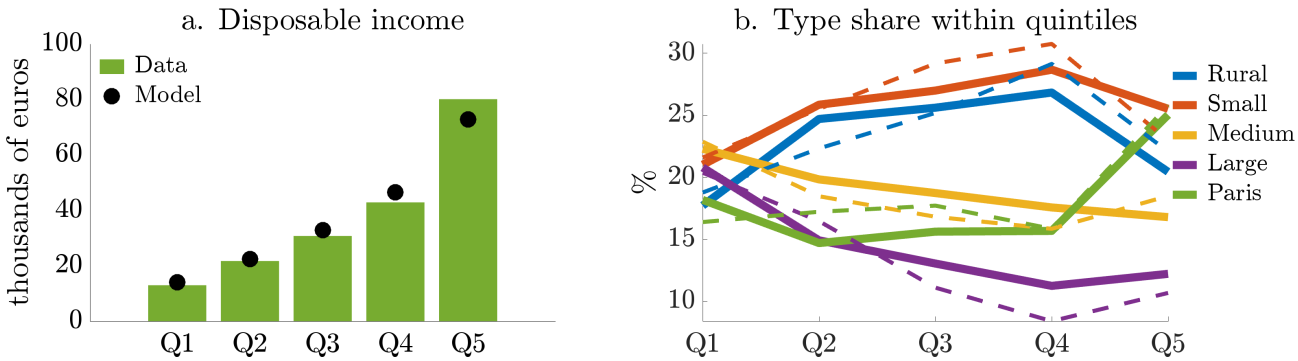
We estimate the elasticity of substitution between energy and G&S consumption to $\sigma = 0.2$, using National Accounts longitudinal data from 1959 to 2021 (the data and method are described in Appendix C). Finally, we set the elasticity of substitution between fossil fuel and electricity to $\epsilon_h = 1.5$. 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 F, we provide robustness check for alternative values of σ, ϵ_h and ϵ_y.

Income process. As changes in transfer, labor and capital incomes account for a large part of the distributive effects of carbon taxation, we calibrate carefully the distribution of each type of income. We fit the disposable income distribution[9] (Figure 5.a), using the AR(1) persistence parameter ρ_z, which is set to be the same across all types. We use the means $\mu_z(k)$ and variances $\sigma_z(k)$ of the idiosyncratic productivity process for each type to match the proportion of each geographical location type within each disposable income quintile (Figure 5.b). Our model recovers that 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 equally distributed,

[9]From the 2021 Insee survey "Revenus et patrimoine des ménages" (RPM 2021).

with over-representation in Q2, Q3 and Q4, and under-representation in Q1 and Q5. Finally, we set the annual discount factor $\beta = 0.94$ to match the French capital-to-income ratio[10] when excluding public debt: $\frac{a}{\text{GDP}} = 4.5$, and the intertemporal elasticity of substitution (IES) $1/\theta$ to 1.

Figure 5: income distribution of households



Notes: Panel a: quintile of disposable income (source: RPM 2021 Insee survey). Panel b: share of each geographical location type within each quintile in data (solid lines, source: BdF 2017 Insee survey) and in the model (dashed lines). Each quintile sums to 100%.

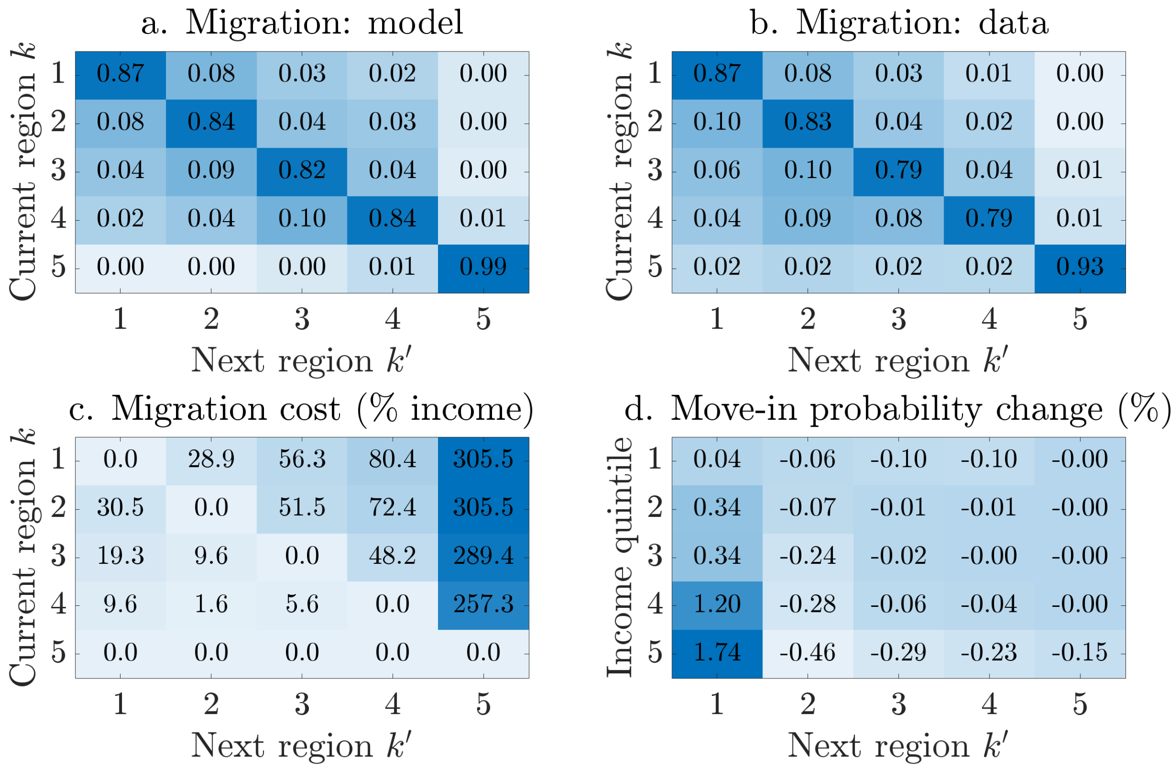
3.2 Migration costs

We use migration costs $\kappa(k, k')$ to recover the empirical probability of migrating from region k to region k'. We first compute the empirical migration matrix over a 5-year horizon.[11] Specifically, we compute the probability of being in region k' at time $t+5$, conditional on being in region k at time t. We then construct a 5×5 migration cost matrix κ to match the empirical migration matrix, normalizing the diagonal to zero to reflect zero cost for staying in the same region. The migration probabilities in the model and in the data are shown in panels a and b of Figure 5. The model fits the data well, and it replicates three key stylized facts. First, on average, 85% of households remain in their current region over a 5-year period, implying an annual migration probability of approximately 3% ($1 - 0.85^{1/5}$). Second, movers tend to relocate to regions of a similar type (*i.e.*, values close to the diagonal), with very few migrations between extremes such as Paris and rural areas. Third, very few people move to Paris, and 93% of current Parisians remain in Paris five years later (or 98.6% after one year).

[10] See 2022 Banque de France report.

[11] To construct this migration matrix, we use the panel dataset BTS-Salariés 2016–2021. We retain only workers aged between 30 and 55, with annual wages above €2,100, and who are present in the dataset throughout the 2016–2021 period. This sample includes 1,010,559 individuals.

Figure 6: Migration matrix and migration parameters



Notes: Panel a and b: probability to have migrated from k towards k' 5 years later, with {1, 2, 3, 4, 5} = {Rural, Small, Medium, Large, Paris}. Sources: panel data from BTS-Salaries 2016-2021. Panel c: migration cost from k to k' in the model, as % of income. Panel d: change in model probability of migrating in region k', following a decrease in average labor income tax rate in region 1, see text.

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 c of Figure 6 presents our migration cost matrix, expressed as a share of GDP per capita. We highlight three important features. First, averaging across the entire matrix (excluding the diagonal), and using population weights, the average (hypothetical) migration cost is 84% of annual income, or approximately €29,000. 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 30% 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 118%, 115%, 92%, 69%, and 0% for rural, small, medium, large, and Paris, respectively. Thus, the smaller the origin region, the higher the expected cost of migration. 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 15%, 10%, 28%, 50% and 289% for rural, small, medium, large, and Paris, respectively. This suggests that the larger and more urbanized the destination, the higher the associated migration cost.

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 panel d 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 to the rural region and less likely to move elsewhere. Moreover, the change in migration probability is much larger for high-income households than for low-income ones. This is because wealthier individuals face lower effective migration barriers and benefit more from lower income taxes due to their higher productivity. In summary, tax changes can induce migration, particularly among richer households. We will return to this mechanism in our results section, when analyzing the effects of carbon taxation—a non-region-specific policy whose impacts differ by location.

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. 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 hydro-electricity 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. The housing supply scaling parameters $\{H_{k=1,2,3,4}\}$ are set to obtain 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. The last parameter H_5 is set to obtain the share of housing in total wealth $H/A = 0.66$. The price elasticity of housing supply is set to $\delta^H = 0.2$, in the range of common values found in the housing model literature (for example 0.1 for Murphy (2018) and 0.3 for Baum-Snow and Han (2024)). Finally, in our main quantitative exercise, 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 is relaxed in Appendix F.

3.4 Fiscal authority

We set lump-sum transfers to $T = 0.08$ to match the share of transfer in each disposable income quintile, as shown in Figure 13.a. We set the labor tax progressivity to $\tau = 0.08$ following Ferriere, Grübener, et al. (2023). Following Auray et al. (2022), λ targets public spending $\bar{G}$ at 29.3% of GDP, we set the effective VAT rate τ^{VAT} to 22.24% and the effective capital income tax rate to 9.02%. The resulting amount of tax paid by each group of households is shown in Figure 13.b. The fit with the data is good, as we mostly miss corporate taxes in the model.

4 Quantitative results

In Section 1, we show that geography is an important determinant of energy consumption for households and firms. In Sections 2 and 3, we build a spatial heterogeneous-agent model, calibrated on France. In this section, we increase carbon taxes τ^h or τ^f and compute the welfare change associated with the transition.

Experiment. The experiment is as follows. We start at the initial steady state as described in Section 3. At $t = 1$, we introduce an unexpected shock to the path of τ^h or τ^f. After $t = 1$, the path is perfectly anticipated by agents. The shock is permanent, with the final tax calibrated to reduce emissions by 10% at the final steady state. The increase in tax is linear: the tax rises from 0 to τ^{final} over 10 periods, and stays at τ^{final} for $t \geq 10$. The carbon tax revenue, in this benchmark experiment, is used to increase public spending; we consider alternative rebating policies in Section 5.

Welfare measure. The welfare is measured as the wealth transfer now that is equivalent to the welfare change during the transition. It answers the question: "what share of my income should I receive now to be indifferent between staying at the initial steady state, or experiencing the transition?". Formally, for each initial wealth a_0, region k_0 and productivity z_0, we find x that satisfies the following equality:

$$\sum_{t=0}^{\infty} \beta^t \mathbb{E}_0[U_{i,t}^{\text{no tax}} | a_0 + x, k_0, z_0] = \sum_{t=0}^{\infty} \beta^t \mathbb{E}_0[U_{i,t}^{\text{tax}} | a_0, k_0, z_0]$$

with $U = \frac{u^{1-\theta}}{1-\theta}$. Finally, we express the wealth equivalent by dividing x by total disposable income: $\text{WE}(a_0, k_0, z_0) = x(a_0, k_0, z_0)/\text{TI}(a_0, k_0, z_0)$[12]. Therefore, a wealth equivalent of -10% means that a household should receive a *one-time* lump-sum transfer equal to 10% of their current income in order to be indifferent between staying at the steady state or going through the transition with the increase in carbon tax. Alternatively, dividing this number by the infinite sum of discount factors $\sum_{t=1}^{\infty} \beta^t \approx 15.7$ gives the transfer a households should receive *every year* in order to be indifferent between staying at the steady state or experiencing the transition.

In this section, we describe the transmission of τ^h and τ^f to household welfare, categorized by income quintile and location. We also examine the role of migration in shaping the distributive effects of carbon taxes, and highlight that the associated costs may differ between the short run and the long run.

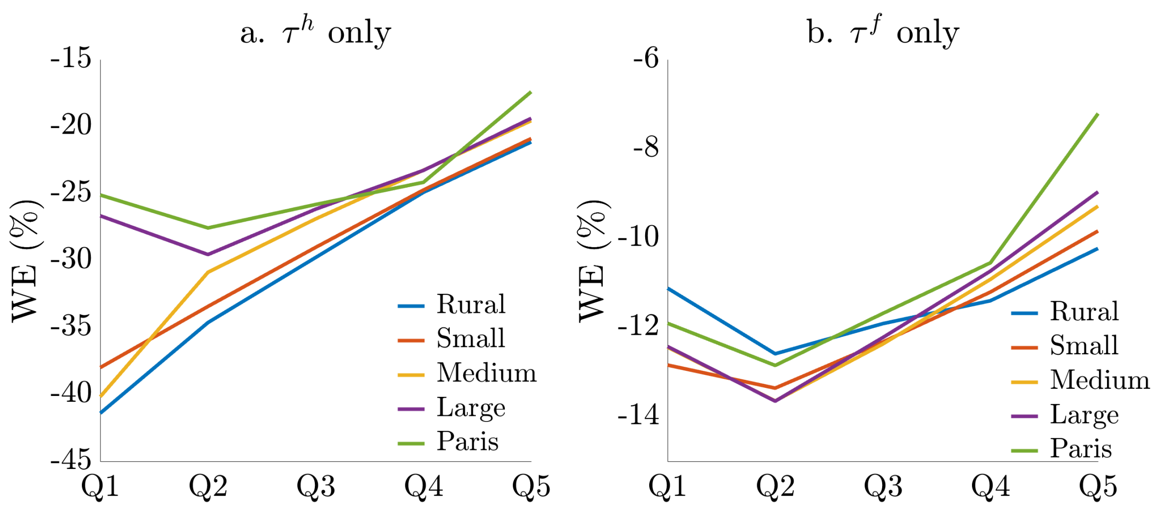
[12] With $\text{TI}(a, k, z) = \Gamma\left(z(k)w(k)\bar{l}\right) + (1 - \tau^k)ra + T(k)$.

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 wealth 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).

Before examining the different channels, we provide some general observations. First, there is a welfare cost associated with reducing emissions by 10%, as the WE is negative, assuming G is not valued by households to isolate the distributive effects of carbon taxation. This cost is higher for τ^h (-27% of initial disposable income on average) than for τ^f (-11% of initial disposable income). This implies that the social planner would need to compensate each individual with a one-time €10,500 transfer to make households accept the increase in τ^h, and €4,250 for the increase in τ^f. Alternatively, the planner should give €673 and €272 transfers every year, respectively, to make households accept the increase in τ^h and τ^f. Second, both taxes are regressive, as the welfare cost is higher for poorer households. The regressivity is significantly more pronounced for τ^h. Third, the welfare cost varies substantially by location. Parisian households tend to experience smaller welfare losses than other regions, regardless of income, while households in small and medium cities consistently face high losses. We now detail the distributive effects of both taxes.

Figure 7: Average welfare effect by region and income



Notes: This represents the average welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition. Panel a: change in τ^h only. Panel b: change in τ^f only.

Carbon tax on households (τ^h). Taxing fossil fuel consumption by households, with few indirect income effects. As shown in the decomposition in Figure 15, the overall welfare impact of τ^h depends on two key factors: the direct effect of the carbon tax, and the change in housing rents p^H. The direct effect of τ^h is more pronounced for households with high fossil fuel consumption, *i.e.*, rural and low-income households. Although households can substitute energy with goods and fossil fuels with electricity, the non-homotheticity of energy consumption with respect to income (ϵ_E) and geography ($\bar{e}$) generates heterogeneous welfare costs. Specifically, the welfare cost is equal to -29.7% of initial disposable income (WE) in rural areas compared to -23.4% WE in Paris, and -34.7% WE for the bottom income quintile (Q1) versus -19.6% WE for the top quintile (Q5). However, this adverse effect on rural households is partially offset by a decline in rents. As some households relocate from small to large cities to avoid the carbon tax, housing price decreases by 6.2% in rural areas and increases by 4.6% in Paris, mitigating the geographic disparity. Thus, while the carbon tax disproportionately burdens rural areas because of energy consumption differences, migration and housing market adjustments alleviate some of this 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 15, 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 3.9% in rural areas compared to a 1.1% decrease in Paris. This results in welfare costs of -17% WE and -5% WE, respectively. The decline in wages disproportionately affects lower-income households, as labor income constitutes a larger share of their total income. As with τ^h, this geographic burden is partially offset by a decrease in housing rents: as households migrate from rural to urban areas seeking higher wages, p^H decreases in rural areas, mitigating losses for households that remain. 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.

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^h or τ^f 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 €149 per ton of CO_2eq for households, and by €117 for firms.[13] At the peak of the EU ETS 1 in 2023, the price of a ton of CO_2 reached €100, which translates into an 8.5% 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 3% decrease in total emissions, provided the EU ETS 2 extension covers all direct household emissions. Therefore, assuming a 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 15% in total emissions, and a welfare cost equal to −28% of initial disposable income (or a one-time equivalent of −€9,850, or −€631 per year).

Robustness checks. Our primary objective is to quantify the redistributive effects of carbon taxes. To this end, we have calibrated the model using relatively low elasticities of substitution, which reflect households' and firms' limited short-run ability to adapt. In Appendix F, we re-run the main experiments using alternative values for key elasticities (σ, σ_y, ϵ_y, ϵ_h, δ_H). We find that the distributional results are largely robust to changes in σ_y, ϵ_y, and δ_H: average welfare losses remain around −17% (in wealth equivalent terms), with rural households facing losses about 20% higher than those in Paris, and households in the bottom income quintile (Q1) experiencing welfare losses 45% higher than those in the top quintile (Q5). The elasticity of substitution between fossil fuels and electricity for households (ϵ_h) plays a somewhat more significant role. Reducing ϵ_h from 1.5 to 1.3 increases overall welfare losses by 3.2 percentage points, as it becomes harder to substitute fossil energy with electricity. The rural/Paris welfare gap also widens slightly, from 18.3% to 18.8%, due to rural households' greater dependence on fossil fuels. The most influential parameter is σ, the elasticity of substitution between energy and other consumption goods. Increasing σ from 0.2 to 0.4 reduces the average welfare cost of carbon taxation by half and significantly lowers the rural/Paris disparity. As energy becomes more easily substitutable, differences in baseline energy consumption matter less for welfare outcomes. These findings suggest that long-run calibrations, featuring greater flexibility and substitution possibilities, may yield different results. They also highlight that the political acceptability of carbon taxation could be enhanced through policies that facilitate adaptation, such as promoting electric vehicles, improving public transportation, and investing in energy-efficient housing.

In conclusion, due to differences in households' energy consumption baskets for τ^h

[13] As firms emit more and exhibit greater elasticity of substitution for clean energy, they require lower taxes to reduce emissions by the same amount.

and firms' fossil fuel 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. In the following section, we further examine the role of migration and the welfare costs over different time horizons.

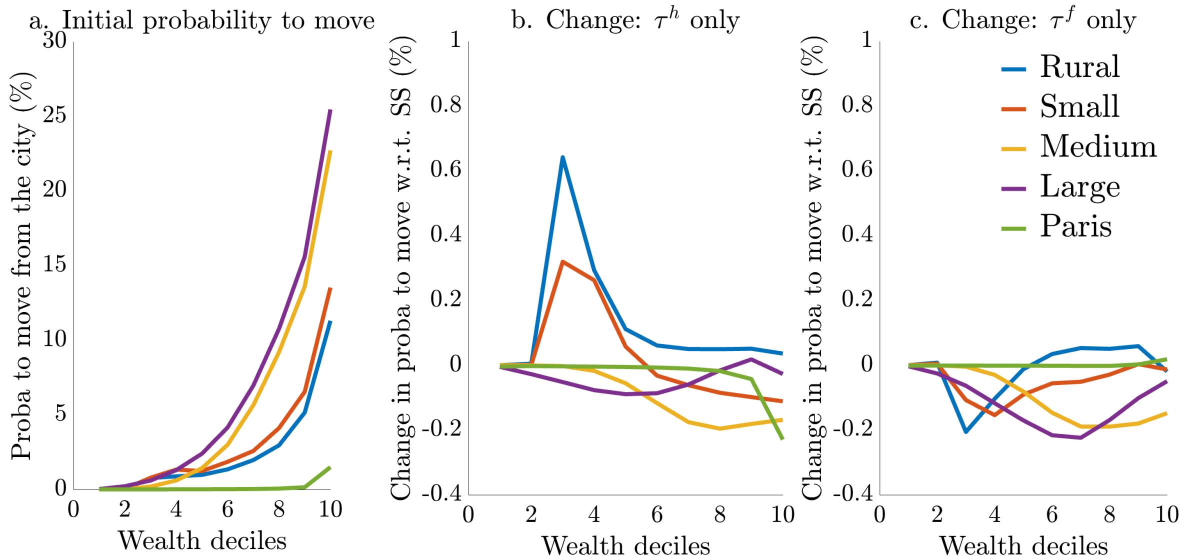
4.2 Migration and welfare

In our spatial model, households can migrate subject to a migration cost $\kappa(k, k')$, which tends to smooth welfare costs between regions over time. In this section, we examine the role of migration in shaping the distributive effects of carbon taxes.

Mobility decisions. Figure 8 illustrates household migration behavior by wealth level and how it changes under our two carbon taxes. Panel a shows that, in the initial steady state, wealthier households are more likely to migrate, due to the presence of fixed migration costs, which disproportionately constrain low-wealth households. Panels b and c report changes in migration decisions during the first period of the transition, relative to the initial steady state. In Panel b, following an increase in the household carbon tax (τ^h), the 20% poorest households in most regions exhibit no change in their migration probability. Lacking the resources to afford moving costs, many of these households remain effectively "trapped." Some respond by increasing savings, either to enable future migration or to buffer future consumption losses. In contrast, middle-wealth households (deciles 3 to 5) in rural and small cities often use their accumulated savings to finance relocation.

Panel c shows that the firm-level carbon tax (τ^f) induces different mobility dynamics. Since this tax operates through income effects, such as lower wages or reduced employment, it leads to a broad decline in migration possibilities across wealth groups and cities. The exception is wealthy households, who have enough wealth to stay mobile and whose labor income is a large share of total income. In Figures 18 and 19 in Appendix, we compare mobility matrices at different stages of the transition for both tax scenarios with the mobility matrix of the initial steady state.

Figure 8: Migration choices by wealth quantiles



Notes: Panel a: probability of leaving the region by wealth decile. Panel b and c: change in migration decisions in the first period of the transition relative to the initial steady state after an increase in τ^h and τ^f, respectively.

As a result of these decision rules, both taxes leads to significant, but different, migration dynamics between region. Figure 17 in Appendix illustrates population shifts between steady states across both income and geographic dimensions. Under τ^h, the increase in energy price encourages poor households to move away from rural areas and small cities, and they are replaced by richer households who can absorb the increase in prices. In the new steady state, average household income increases by 2.4% in rural areas and 1.1% in small cities relative to the initial equilibrium, but falls by 3% in large cities, highlighting interregional recomposition effects.

The migration dynamics is the opposite for τ^f. As wages decline by 4% in small cities compared to only 1% in Paris, high-productivity workers migrate from small to large cities. They are replaced by low-productivity households for whom the wage decline has a smaller impact, as transfers constitute a larger share of their income. In the new steady state, average income is 5.5% lower in rural areas and 2.8% lower in small cities relative to the initial equilibrium, but increases by 1.6% in medium cities and 4.2% in large cities.

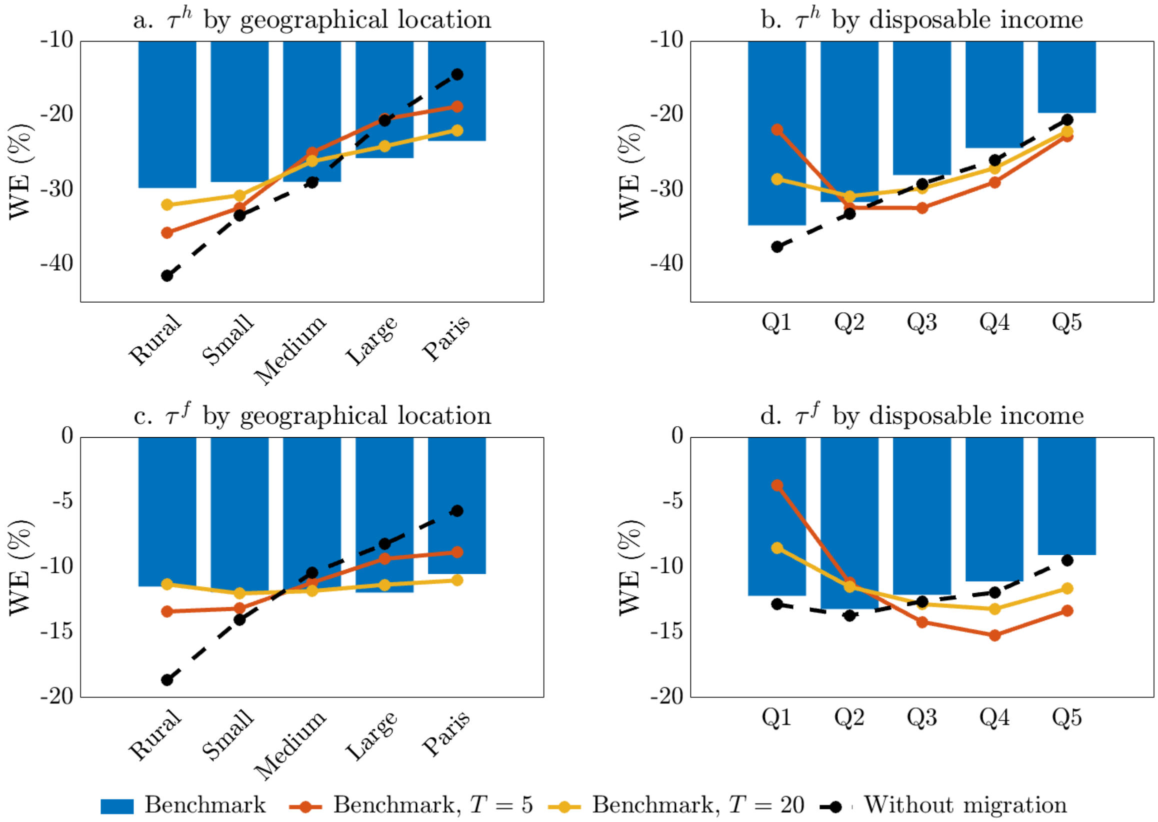
Short-run and long-run welfare effects. Migration shapes the geographic distributional effects of carbon taxes, but this adjustment takes time, as households need to accumulate savings to cover migration costs or wait for a favorable productivity shock. As a result, welfare effects differ between short-run and long-run horizons. To approximate short-run welfare effects, we compute welfare over a finite horizon by truncating the infinite sum of discounted utility. Formally, for a given T, we solve the following equation:

$$\sum_{t=0}^{T} \beta^t \mathbb{E}_0[U_{i,t}^{\text{no tax}} | a_0 + x, k_0, z_0] = \sum_{t=0}^{T} \beta^t \mathbb{E}_0[U_{i,t}^{\text{tax}} | a_0, k_0, z_0]$$

and scale the x obtained by total income, as explained above. Furthermore, to facilitate comparisons, we normalize the "horizon-T wealth equivalent" to have the same mean as the "infinite-horizon WE," since welfare costs accumulate over time. This metric indicates the share of income required to compensate a household for the welfare cost incurred over the first T periods of the transition.

The red and yellow lines in Figure 9 represent the wealth equivalent (WE) for $T = 5$ years and $T = 20$ years, while the blue bars correspond to $T = \infty$. As shown, the distributive effects differ significantly between the short run and the long run. At $T = 5$, welfare losses are significantly higher for rural households than for urban ones, and much lower for poor households than for rich ones. In the short run, rural households bear the cost of carbon taxes but have not yet migrated. Since regional population adjustments described above have not yet fully occurred, the cost of τ^h and τ^f is concentrated in the middle of the income distribution, as shown in the decomposition for the 5-year horizon in Figure 16 in Appendix. This "U-shape" pattern aligns with panel b of Figure 5, which shows that rural households are concentrated in the middle of the income distribution, whereas Parisian households are concentrated at the tails. Another reason for this U-shape is the fact that the real interest rate decreases a lot in the first periods, affecting low-income households less.

Figure 9: Welfare effect with and without migration, and at different horizons



Notes: This represents the average welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different horizons or without migration. Results of different horizons are scaled for comparison. Panels *a* and *c*: change in τ^h only. Panels *b* and *d*: change in τ^f only.

Counterfactual without migration. In Figure 9, we conduct the same experiments as above (keeping the same target of -10% in total emissions) but restrict households from migrating (formally, we set $\kappa = \infty$). The blue bars represent the results of our benchmark with migration, while the black dashed line reflects the scenario without migration. We observe that, although migration does not significantly affect welfare costs across the income dimension, it substantially reduces disparities along the geographical dimension. Without migration, rural areas face welfare costs equal to -42% WE of initial disposable income for τ^h and -19% WE for τ^f, compared to -30% WE and -12% WE with migration. The opposite effect is observed in large cities: they attract households from rural areas seeking to avoid the carbon tax, which pushes housing rents up, and real wages down. Therefore, welfare costs in Paris are significantly higher with migration than without. These results highlight the critical role of migration in shaping the distributional effects of carbon taxes.

In conclusion, we have shown that **the cost of the carbon transition for house-**

holds heavily depends on income, geography, and the type of taxes. Rural areas and poor households tend to experience higher losses compared to urban and wealthy households. **Migration plays a significant role in shaping and smoothing these losses** across the geographic dimension. Finally, the population recomposition within regions occurs gradually, implying that geographic disparities are more pronounced in the short run than in the long run.

5 Optimal transfer policies

The distributive effects of carbon taxation are key 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 address the normative question of the optimal use of carbon tax revenue through targeted lump-sum transfers. Our fiscal system offers multiple ways to recycle the revenue, such as lowering existing taxes or investing in measures to mitigate incompressible energy consumption. However, we argue that transfers are essential for communication and political acceptability. By explicitly separating carbon tax revenue from the state budget, transfers make clear that the tax aims to influence behavior rather than finance public deficits.

We consider four scenarios, each targeting a 10% ex-post reduction in emissions between the initial and final steady states. We assume both taxes are equal, *i.e.* $\tau^h = \tau^f$ (in Appendix E, we also consider scenarios with $\tau^h \neq \tau^f$). The transfer rule in each scenario is the following[14]:

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

where T is the transfer, y_i the total household's income, CTR the carbon tax revenue, and μ the scaling parameter[15].

In the "**Benchmark *G***" scenario, the carbon tax revenue is used to increase public spending G (that are not valued by households), with transfers set to zero. In the

[14]We also computed results for the additive rule $T(y, k) = (x_k + y^{-x}) \cdot CTR \cdot \mu$, but found that it yields a lower welfare than scenario 4. Moreover, in Appendix E, we consider an alternative rule to account for progressivity.

[15]Total income: $y = \Gamma(zwl) + (1 - \tau^k)ra + \bar{T}$. Carbon tax revenue: $CTR = \tau^h(1 + \tau^{\text{VAT}})F^h + \tau^f(F^y + F^N)$. Scaling parameter: $\mu = 1/\int_i y_i^{-x_k}$.

"**Uniform**" scenario, all households receive the same transfer. In the "**Income**" scenario, we find the optimal value[16] of x to maximize welfare, as defined in Section 4. This scenario assumes the government knows household income and can implement a progressive transfer (if $x > 0$) but cannot differentiate based on location k (or is legally restricted from doing so, as in France). Finally, in the "**Income $\times$ Geography**" scenario, we optimize over five different x_k, allowing the government to apply region-specific progressivity levels during the transition.

In Table 2, we show the median welfare for each scenario, by location and by income. We choose the median welfare as we are interested in the political acceptability of carbon taxes. In Appendix E, we show that we obtain the same qualitative results taking average welfare as a target, using Negishi weights, or with alternative rebate formulas.

Table 2: Median welfare change by location and income

	Scenario	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**All**
(1)	Benchmark G	−17.3	−17.4	−15.4	−15.3	−14.5	−16.1
(2)	Uniform	6.4	6.7	7.9	10.3	7.3	7.3
(3)	Income	7.5	7.5	10.1	13.3	10.4	9.4
(4)	Income × Geography	7.5	7.9	13.4	24.1	11.8	10.1
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**
(1)	Benchmark G	−18.2	−19.1	−17.7	−15.3	−12.8	−16.1
(2)	Uniform	20.3	12.5	7.21	3.0	0.9	7.3
(3)	Income	66.7	26.5	6.2	−2.0	−0.7	9.4
(4)	Income × Geography	94.8	31.7	7.5	−1.3	0.1	10.1

Notes: This represents the median welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different rebating policies.

Our benchmark scenario yields welfare losses, as the revenue is used to increase G that is not valued by households. This is the most natural choice to study the distributive effects of carbon taxation, as introducing G in the utility function would directly affect inequality and distort the analysis. Therefore, replacing this inefficient use of carbon tax revenue with a uniform transfer naturally yields a higher utility: the comparison is more relevant for the distributive effects, and the welfare ratios between areas or income quintiles. Moreover, for our calibration, transfers are welfare-improving: a uniform transfer policy increases median welfare by 7.3% (WE). As transfers redistribute resources from high-income households with low marginal utility to low-income households with high marginal utility, they increase aggregate utilitarian welfare (in

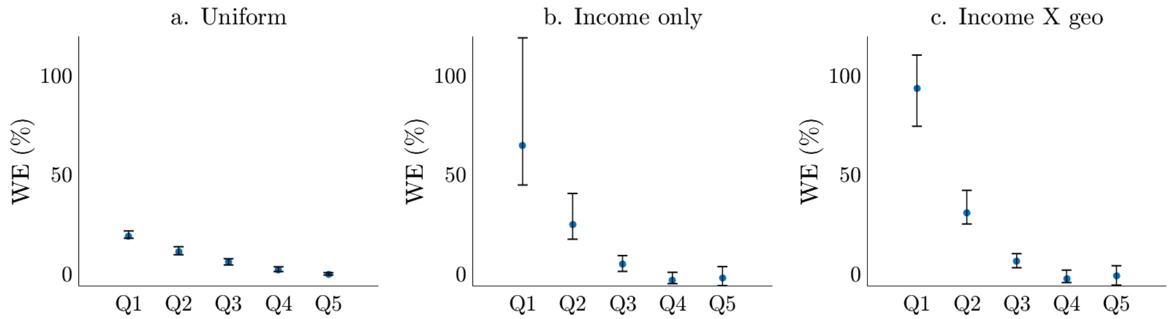
[16]Scenario 3: $x = 2.15$. Scenario 4: $x_k = [2.07, 2.08, 2.38, 2.4, 2.27]$.

Appendix E, we also use Negishi weights to neutralize the redistribution motive). Additionally, they mitigate inefficiencies arising from the borrowing constraint by providing some insurance to low-income households, which further increases welfare. Hence, the welfare gains stem from the model's baseline calibration, and the relevant comparison is between our different transfer scenarios, not between T and G.

Although a uniform transfer raises median welfare, an optimal progressive transfer targeting low-income households yields a 29% higher welfare gain (raising WE +9.4%), at the expense of high-income groups. However, as shown in Appendix Table 13, the "**Income**" scenario also generates welfare losses for 24.2% of households, primarily in rural areas and small cities. These are primarily high-income households who do not benefit from the progressive transfer yet still bear the tax burden.

We therefore introduce the "**Income** $\times$ **Geography**" scenario, which allows transfer progressivity to vary by region. Relative to the income-only rule, this policy improves welfare by increasing progressivity in large cities and reducing it in rural areas and small towns. It raises median welfare across all income and geographic groups and reduces the share of households experiencing welfare losses by 10 percentage points compared to the income-only scenario. These gains stem from the fact that rural households are concentrated around the middle of the income distribution, whereas the lowest- and highest-income households are overrepresented in large urban areas. Allowing for region-specific progressivity better aligns transfers with local income profiles and reduces the dispersion of welfare gains. Figure 10 presents the 25th, 50th and 75th percentiles of the welfare gain distribution within each income quantile. Compared to the income-only policy, the Income $\times$ Geography rule notably reduces the dispersion of welfare gains within the bottom quintile (Q1). As a result, incorporating geographic variation into redistribution policies raises median and average welfare gains by 7.4% (+10.1% WE) and 7.6% (+29.8% WE), respectively, relative to the optimal transfer based solely on income. While this policy does not increase median welfare in rural areas overall, it redistributes gains toward middle- and high-income households within those areas.

Figure 10: Distribution of welfare gains within income quintiles



Notes: This represents the 25th, 50th and 75th percentiles of the welfare gain distribution (one-time wealth-equivalent transfer expressed in % of households' disposable income) within each income quintile over the transition, for different transfer policies.

As shown in Figure 20 in the Appendix, our different rebating rules yield different migration and composition effects across income groups and regions. In the "**Income**" scenario, many high-income households migrate from rural and small areas to medium and large cities, while lower-income households move in the opposite direction due to declining rents. In contrast, this effect is mitigated in the "**Income** $\times$ **Geography**" scenario: since transfers are less progressive in rural and small areas and more progressive in medium and large cities, rich households from rural areas and poor households from urban regions have fewer incentives to migrate.

We show that **it is possible to reduce emissions while mitigating the welfare losses** associated with the green transition. By implementing transfers based on income and location, the share of households experiencing welfare losses can be reduced, thereby enhancing the political acceptability of carbon taxes.

6 Conclusion

In this paper, we study the distributive effects of carbon taxation with a focus on spatial heterogeneity. Using both household-level surveys and matched employer-employee data from France, we document that rural households consume 2.8 times more fossil fuels than urban households and are employed in firms that emit 2.7 times more. These patterns are consistent across other countries. We incorporate these findings into a spatial heterogeneous agent model, featuring idiosyncratic income risks, endogenous savings, and migration choices, as well as segmented housing and labor markets, and local energy expenditure shares for both households and firms. Our approach contributes to bridging a gap between spatial models, which emphasize migration decisions, and heterogeneous-agent models that analyze inequality and wealth accumulation.

We find that rural households bear a disproportionate burden from carbon taxation. In our benchmark scenario, their welfare losses are 20% higher than those of Parisian households. Ignoring spatial heterogeneity in income-based transfer policies reduces welfare gains by 7%, a result robust to different welfare criteria and rebate schemes. These findings highlight a key policy implication: geographical location must be explicitly accounted for when designing carbon tax frameworks, 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 optimal 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. Finally, our findings indicate that different forms of carbon taxation generate distinct migration responses, highlighting the need for further empirical research.

References

Agrawal, David R and Foremny, Dirk (2019). "Relocation of the rich: Migration in response to top tax rate changes from Spanish reforms". In: *Review of Economics and Statistics* 101.2, pp. 214–232 (cit. on p. 21).

Aiyagari, S. Rao (1994). "Uninsured Idiosyncratic Risk and Aggregate Saving". In: *Quarterly Journal of Economics* 109.3, pp. 659–684 (cit. on pp. 5, 12).

Akcigit, Ufuk, Baslandze, Salomé and Stantcheva, Stefanie (2016). "Taxation and the international mobility of inventors". In: *American economic review* 106.10, pp. 2930–2981 (cit. on p. 21).

Artuç, Erhan, Chaudhuri, Shubham and McLaren, John (2010). "Trade shocks and labor adjustment: A structural empirical approach". In: *American economic review* 100.3, pp. 1008–1045 (cit. on p. 20).

Auclert, Adrien, Bardóczy, Bence, Rognlie, Matthew and Straub, Ludwig (2021). "Using the sequence-space Jacobian to solve and estimate heterogeneous-agent models". In: *Econometrica* 89.5, pp. 2375–2408 (cit. on p. 49).

Auclert, Adrien, Monnery, Hugo, Rognlie, Matthew and Straub, Ludwig (2023). *Managing an energy shock: Fiscal and monetary policy.* Tech. rep. National Bureau of Economic Research (cit. on p. 5).

Auray, Stéphane, Eyquem, Aurélien, Garbinti, Bertrand and Goupille-Lebret, Jonathan (2022). "Markups, Taxes, and Rising Inequality". In: *CREST Working Paper* (cit. on pp. 22, 50).

Bach, Laurent, Dutronc-Postel, Paul, Guillouzouic, Arthur, Malgouyres, Clément and Paya, Rachel (2024). "Les émissions de CO2 de l'industrie française et le ciblage carbone des politiques publiques". In: *IPP Working Paper* 102 (cit. on pp. 42, 45, 46).

Barrage, Lint (2020). "Optimal dynamic carbon taxes in a climate–economy model with distortionary fiscal policy". In: *Review of Economic Studies* 87.1, pp. 1–39 (cit. on pp. 4, 5).

Baum-Snow, Nathaniel and Han, Lu (2024). "The microgeography of housing supply". In: *Journal of Political Economy* 132.6, pp. 1897–1946 (cit. on p. 22).

Bayer, Christian, Kriwoluzky, Alexander, Müller, Gernot J and Seyrich, Fabian Georg Ludwig (2025). *Redistribution within and across borders: The fiscal response to an energy shock.* Tech. rep. ECON-tribute Discussion Paper (cit. on p. 5).

Boehm, Johannes, Fize, Etienne and Jaravel, Xavier (2025). "Five facts about MPCs: Evidence from a randomized experiment". In: *American Economic Review* 115.1, pp. 1–42 (cit. on p. 53).

Bryan, Gharad and Morten, Melanie (2019). "The aggregate productivity effects of internal migration: Evidence from Indonesia". In: *Journal of Political Economy* 127.5, pp. 2229–2268 (cit. on p. 20).

Casey, Gregory (2024). "Energy efficiency and directed technical change: implications for climate change mitigation". In: *Review of Economic Studies* 91.1, pp. 192–228 (cit. on pp. 14, 52).

Cette, Gilbert, Koehl, Lorraine and Philippon, Thomas (2019). "Labor Shares in Some Advanced Economies". In: *Working Paper # 727, Banque de France* (cit. on pp. 22, 50).

Chan, Jenny, Diz, Sebastian and Kanngiesser, Derrick (2024). "Energy prices and household heterogeneity: Monetary policy in a gas-tank". In: *Journal of Monetary Economics* 147, p. 103620 (cit. on p. 5).

Clemens, Michael A, Montenegro, Claudio E and Pritchett, Lant (2019). "The place premium: Bounding the price equivalent of migration barriers". In: *Review of Economics and Statistics* 101.2, pp. 201–213 (cit. on p. 20).

Comin, Diego, Lashkari, Danial and Mestieri, Martí (2021). "Structural Change With Long-Run Income and Price Effects". In: *Econometrica* 89.1, pp. 311–374 (cit. on pp. 5, 13, 17, 50, 52).

Couture, Victor, Gaubert, Cecile, Handbury, Jessie and Hurst, Erik (2024). “Income growth and the distributional effects of urban spatial sorting”. In: *Review of Economic Studies* 91.2, pp. 858–898 (cit. on p. 5).

Cronin, Julie Anne, Fullerton, Don and Sexton, Steven (2019). “Vertical and Horizontal Redistributions from a Carbon Tax and Rebate”. In: *Journal of the Association of Environmental and Resource Economists* 6 (S1) (cit. on p. 4).

Desmet, Klaus and Rossi-Hansberg, Esteban (2014). “Spatial Development”. In: *American Economic Review* 104.4, pp. 1211–1243 (cit. on p. 5).

Douenne, Thomas (2020). “The Vertical and Horizontal Distributive Effects of Energy Taxes: a Case Study of a French Policy”. In: *Energy Journal* 43.3, pp. 231–254 (cit. on p. 4).

Fajgelbaum, Pablo D, Morales, Eduardo, Suárez Serrato, Juan Carlos and Zidar, Owen (2019). “State taxes and spatial misallocation”. In: *Review of Economic Studies* 86.1, pp. 333–376 (cit. on p. 5).

Ferriere, Axelle, Grübener, Philipp, Navarro, Gaston and Oliko, Vardishvili (2023). “On the Optimal Design of Transfers and Income Tax Progressivity”. In: *Journal of Political Economy Macroeconomics* 1, pp. 276–333 (cit. on pp. 22, 61).

Ferriere, Axelle and Navarro, Gaston (2025). “The heterogeneous effects of government spending: It’s all about taxes”. In: *Review of Economic Studies* 92.2, pp. 1061–1125 (cit. on pp. 12, 48, 50).

Ferriere, Axelle, Navarro, Gaston, Reyes-Heroles, Ricardo, et al. (2018). “Escaping the losses from trade: The impact of heterogeneity on skill acquisition”. In: *2018 meeting papers*. Vol. 1248. Society for Economic Dynamics (cit. on p. 5).

Fried, Stephie (2018). “Climate policy and innovation: A quantitative macroeconomic analysis”. In: *American Economic Journal: Macroeconomics* 10, pp. 90–118 (cit. on pp. 22, 50).

Fried, Stephie, Novan, Kevin and Peterman, William B (2024). “Understanding the Inequality and Welfare Impacts of Carbon Tax Policies”. In: *Journal of the Association of Environmental and Resource Economists* 11.S1, S231–S260 (cit. on pp. 4, 18).

Giannone, Elisa, Li, Qi, Paixao, Nuno and Pang, Xinle (2023). *Unpacking moving: A quantitative spatial equilibrium model with wealth*. Tech. rep. Bank of Canada Staff Working Paper (cit. on p. 5).

Golosov, Mikhail, Hassler, John, Krusell, Per and Tsyvinski, Aleh (2014). “Optimal Taxes on Fossil Fuel in General Equilibrium”. In: *Econometrica* 82.1, pp. 41–88 (cit. on p. 52).

Goulder, Lawrence H., Hafstead, Marc A.C., Kim, GyuRim and Long, Xianling (2019). “Impacts of a carbon tax across US household income groups: What are the equity-efficiency trade-offs?” In: *Journal of Public Economics* 175, pp. 44–64 (cit. on p. 4).

Greaney, Brian (2023). “Homeownership and the Distributional Effects of Uneven Regional Growth”. In: *Available at SSRN 4406024* (cit. on p. 5).

Hassler, John, Krusell, Per and Olovsson, Conny (2021). “Directed technical change as a response to natural-resource scarcity”. In: *Journal of Political Economy* 129, pp. 3039–3066 (cit. on pp. 14, 18, 51, 52).

Heathcote, Jonathan, Storesletten, Kjetil and Violante, Giovanni (2017). “Optimal Tax Progressivity: An Analytical Framework”. In: *Quaterly Journal of Economics* 132.4, pp. 1693–1754 (cit. on p. 16).

Känzig, Diego R. (2023). “The Unequal Economic Consequences of Carbon Pricing”. In: *NBER Working Paper* (cit. on p. 4).

Kaplan, Greg, Moll, Benjamin and Violante, Giovanni (2018). “Monetary Policy According to HANK”. In: *American Economic Review* 108 (3), pp. 697–743 (cit. on p. 50).

Kennan, John and Walker, James R (2011). “The effect of expected income on individual migration decisions”. In: *Econometrica* 79.1, pp. 211–251 (cit. on p. 20).

Lafrogne-Joussier, Raphaël, Martin, Julien and Mejean, Isabelle (2023). “Energy cost pass-through and the rise of inflation: Evidence from French manufacturing firms”. In: (cit. on p. 14).

Langot, François, Malmberg, Selma, Tripier, Fabien and Hairault, Jean - Olivier (2023). “The Macroeconomic and Redistributive Effects of Shielding Consumers from Rising Energy Prices: the French Experiment”. In: *Working Paper, CEPREMAP* (cit. on p. 5).

Martinez, Isabel (2017). “Beggar-thy-neighbour tax cuts: Mobility after a local income and wealth tax reform in Switzerland”. In: *Luxembourg Institute of Socio-Economic Research (LISER) Working Paper Series* 8 (cit. on p. 21).

Mathur, Aparna and Morris, Adele C. (2014). “Distributional effects of a carbon tax in broader U.S. fiscal reform”. In: *Energy Policy* 66, pp. 326–334 (cit. on p. 4).

Murphy, Alvin (2018). “A dynamic model of housing supply”. In: *American economic journal: economic policy* 10.4, pp. 243–267 (cit. on p. 22).

Papageorgiou, Chris, Saam, Marianne and Schulte, Patrick (2017). “Substitution between Clean and Dirty Energy Inputs: A Macroeconomic Perspective”. In: *Review of Economics and Statistics* 99.2, pp. 281–290 (cit. on pp. 18, 22).

Pieroni, Valerio (2023). “Energy shortages and aggregate demand: Output loss and unequal burden from HANK”. In: *European Economic Review* 154, p. 104428 (cit. on p. 5).

Rausch, Sebastian, Metcalf, Gilbert E. and Reilly, John M. (2011). “Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households”. In: *Energy Economics* 33 (Supp 1), S20–S33 (cit. on p. 4).

Tauchen, George (1986). “Finite state markov-chain approximations to univariate and vector autoregressions”. In: *Economics letters* 20.2, pp. 177–181 (cit. on p. 47).

Young, Cristobal and Varner, Charles (2011). “Millionaire migration and state taxation of top incomes: Evidence from a natural experiment”. In: *National Tax Journal* 64.2, pp. 255–283 (cit. on p. 21).

Appendix

Table of contents

A Descriptive Evidence

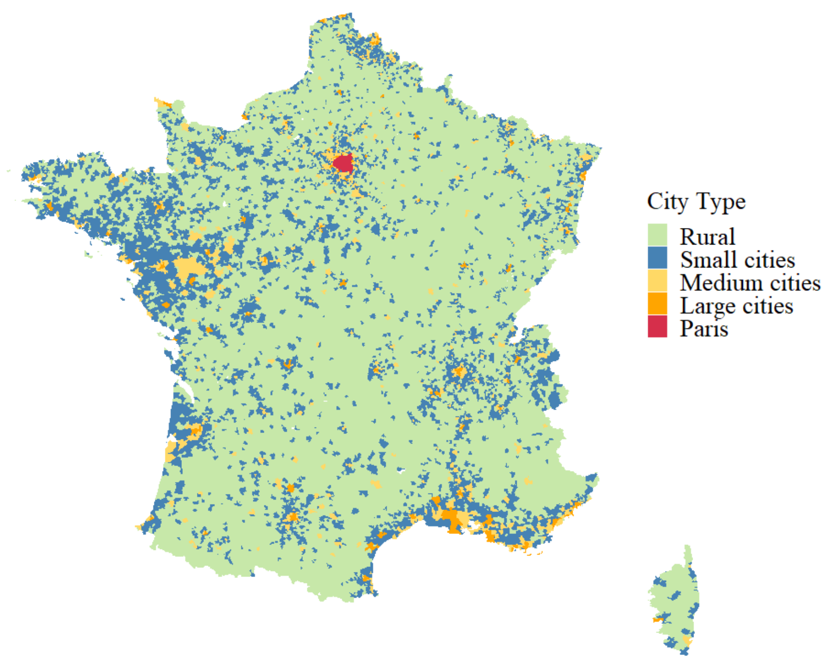
A.1 City types

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 11 provides a map of France illustrating these categories, using 2024 Insee geographical code.

Figure 11: 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 3 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: housing (and we show the share of population living in a house) and 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: Descriptive statistics: households consumption, BdF 2017

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
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

Notes. 16,739 households, weighted using survey weights.

Spatial distribution of 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 Figure 3.

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, BdF 2017

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

Notes. 16,739 households, weighted using survey weights.

Energy shares in other countries: Table 1 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.

We use the Consumer Expenditure Survey (CES) 2023 for the US. We use the latest tables publicly available. For the US, 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.

A.3 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 Insee 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 5 and 6.

Table 5: 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 5 we show the share of workers in each sector, by city types and by income quintiles. In Table 6, 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 6: 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
		$\frac{tCO_2}{Workers}$	% 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.

Spatial distribution of sectoral emissions. Using the 2022 BTS, we can visualize emissions per worker by geographical location at a very granular level. In 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.

A.4 Predicted energy shares and emissions

OLS Regressions. Table 3 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:

$$y_i = \alpha + \sum_{q=1}^{5} \beta_q \mathbb{I}_{Q_i=q} + \sum_{k=1}^{5} \gamma_k \mathbb{I}_{C_i=k} + \mu * \text{Controls}_i + \epsilon_i \tag{6}$$

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 7 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 7: 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 (6). 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.

*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

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 5 seconds to compute on a personal computer, and 27 seconds for a non-linear transition between two distinct steady states. The entire code has been written from scratch on Matlab.

Heterogeneous-agent structure. Our state-space for asset, income and geography is $\mathbb{S} = \mathbb{A} \times \mathbb{Z} \times \mathbb{K}$. We discretize $\mathbb{A}$ over an exponential grid of 100 points between 0 and 40, $\mathbb{Z}$ over 5 points using Tauchen (1986) method, and $\mathbb{K} = \{1, 2, 3, 4, 5\}$, which gives us 2,500 grid points. We solve the household decision using value function iteration (VFI). The key variable of choice for the household is the implicit utility $u(a, k, z)$: given u, k' and the first-order conditions, the households can choose its consumption c, e^h, N^h, F^h, H, and the budget constraint gives the saving choice a' as a residual. To solve the VFI, the follow these steps:

1. for each choice $k' \in \mathbb{K}$, use a golden-section algorithm to find the implicit utility $u^{k'}(a, k, z)$ such that $a' = 0$, to obtain a lower bound for the maximization of the utility.
2. guess the expected value function $f(a, k, z) = \mathbb{E}[V(a, z, k)]$.
3. for each choice $k' \in \mathbb{K}$, use a golden-section algorithm to find the implicit utility $u^{k'}(a, k, z)$ that maximizes the value function $U^{k'}(a, k, z) + \beta f(a', k', z')$.
4. using Gumbel trick described below, find the new value function $V(a, k, z)$.
5. using spline interpolation over $V(a, k, z)$, compute the new guess for the value function $f(a, k, z)$.
6. use the Howard's improvement: for 30 iterations, iterate the f guess without optimizing, taking $f^{new}(a, k, z) = u^{k'}(a, k, z) + \beta f(a, k, z)$.
7. compare the new value function f^{new} with the guess $f(a, k, z)$: 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 (a, k, z) and (a', k', z'). 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 $2 * 5 * 5$ values that are the products of:

- **a**: for the household's decision $a'(a, k, z)$, 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'.

Note that we use a sparse matrix M, as each column contains only 50 values over 2,500 lines. 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 $V_t^{k'}(a,z,k)$ the value function for the household at the grid point (a,z,k) choosing the future location k'. Let $\epsilon_{k'}$ the preference shock for each location k', and assume the vector $\overrightarrow{\epsilon} = \{\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4, \epsilon_5\}$. Then the complete value function is the expectation of all k'-value function, taken over $\overrightarrow{\epsilon}$:

$$V_t(a,z,k) = \mathbb{E}_{\overrightarrow{\epsilon}}\left[\max_k \left\{V_t^{k'}(a,z,k)\right\}\right] = \varrho \ln\left(\sum_{k' \in \mathbb{K}} \exp\left(\frac{V_t^{k'}(a,z,k)}{\varrho}\right)\right)$$

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

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

High number of guesses. We need $n_g = 13$ guesses to solve our model, at the steady state and during the transition: interest rate R (asset market), total electricity N (electricity market), housing rents$\{p_1^H, p_2^H, p_3^H, p_4^H, p_5^H\}$ (segmented housing markets), local outputs $\{Y_1, Y_2, Y_3, Y_4, Y_5\}$ (segmented labor markets), and carbon tax revenue CTR (government budget constraint). For the calibration procedure, we use more than 30 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 (100-1 in our experiment), of any variable i (13), on any clearing condition j (13), at any time $t^{clearing}$ (99), leading to a matrix $J = 1287 \times 1287$. 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 8: Table of parameters

Parameter	Description	Value	Notes and targets
Households			
β	Discount factor	0.94	$\frac{a}{\text{GDP}} = 4.5$
θ	Intertemporal ES	1	Kaplan, Moll and Violante (2018)
σ	ES between c and e^h	0.2	Estimated in Appendix C
Λ_E	Energy share	0.095	Energy share in consumption = 9.5%
Λ_H	Housing rents share	1.464	Housing spending share in consumption = 17%
ϵ_E	Non-homotheticity parameter	0.9	Energy expenditures across income quintiles
ϵ_H	Non-homotheticity parameter	0.25	Housing expenditures across income quintiles
Λ_C, ϵ_C	Utility parameters	1	Comin, Lashkari and Mestieri (2021)
$\gamma_h(k)$	Fossil share	$[0.83, 0.81, 0.81, 0.80, 0.73]$	Fossil fuel share in consumption in each k
ϵ_h	ES between F^h and N^h	1.5	Authors choice
H_k^s	Housing supply	[0.43, 0.46, 0.29, 0.20, 0.32]	Population in each city type
$\bar{e}(k)$	Energy incompressible use	$0.01 * [1.82, 1.43, 1.30, 0.59, 0]$	Energy share across types
$\rho_{\mathcal{G}}$	Gumbel shock variance	0.1	Income heterogeneity, aggregate
ρ_z	Persistence z	0.97	Income heterogeneity, aggregate
$\mu_z(k)$	Mean z	[-0.09,-0.07,0.09,0.14,0.04]	Average income for each type
$\sigma_z(k)$	Variance z	[0.29,0.29,0.28,0.27,0.40]	Heterogeneity within each type
$\underline{a}$	Borrowing constraint	0	Authors' choice
Firms			
p^F	Price of fossil fuel	0.6773	Share of fossil fuel imports = 4%
$\omega_y(k)$	Energy share	$[0.09, 0.07, 0.05, 0.04, 0.02]$	Share of each regional firm in total emissions
σ_y	ES between e^y and (K, l)	0.05	Fried (2018)
α	Capital share	0.3089	$\frac{wl}{GDP}$ from Cette, Koehl and Philippon (2019)
γ_y	Share of fossil in Y mix	0.86	Firms' share in total emissions = 62.5%
ϵ_y	ES between F^y and N^y	1.5	Fried (2018)
Government			
$\bar{T}$	Transfers	0.08	Share of T in income
τ	Labor tax progressivity	0.08	From Ferriere and Navarro (2025)
λ	Labor tax level	0.571	$\frac{\bar{G}}{GDP} = 0.29$ as in Auray et al. (2022)
τ^k	Corporate income tax rate	9.02%	Effective rate in Auray et al. (2022)
τ^{VAT}	VAT tax rate	22.34%	Effective rate in Auray et al. (2022)

C.1 Data on income

For Figure 4, we use Enquête Budget des Familles 2017. For Figure 5.a, we use the average disposable income by decile from Revenus et patrimoine des ménages, Édition 2021. For Figure 5.b, we use fiscal data in 2021 total income as reproduced below:

Table 9: 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

For Figure 13, we use the *Revenus et patrimoine des ménages, Édition 2021*, that we reproduce below:

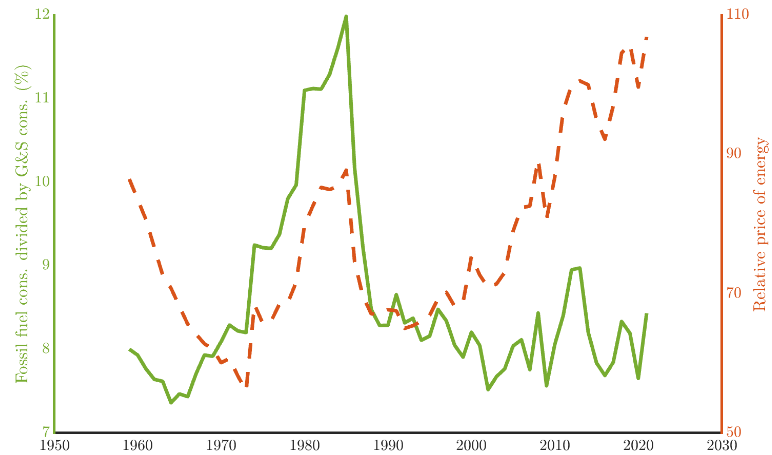
Table 10: Revenues and taxes by income decile (thousand euros)

	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

C.2 Household energy consumption: estimation of σ

In Figure 12, we use French longitudinal aggregate data taken from Insee 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 12: 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:

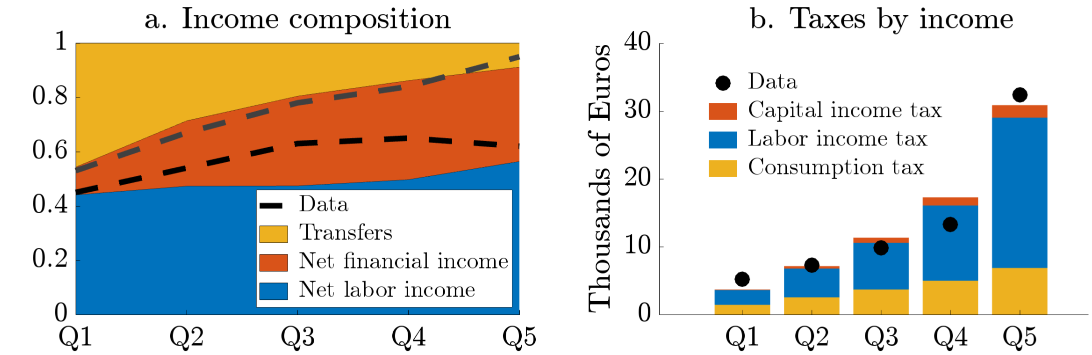
$$\Delta \ln(e_t^h) - \Delta \ln(c_t) = -\sigma \Delta \ln(p_t^h) + \epsilon_t$$

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 Other untargeted moments

In this section, we present untargeted moments of our model. In Figure 13, we show the income composition across income quintile, and total taxes paid by households.

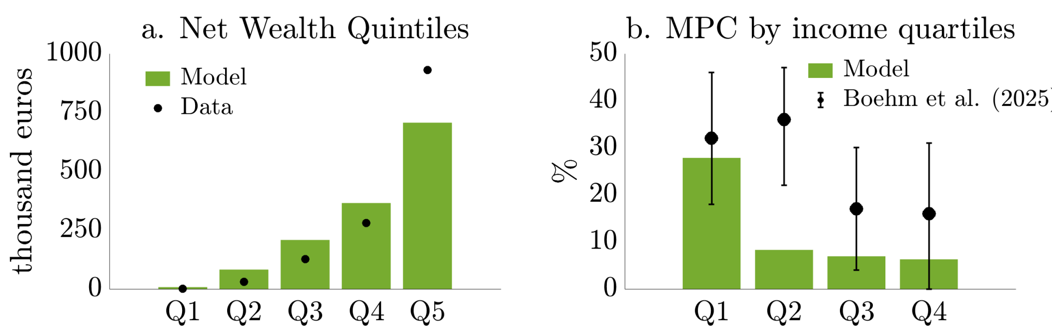
Figure 13: Income composition and taxes by income quintile



Notes: Panel *a*: composition of income data and model fit. Panel *b*: taxes paid by households in the model and data (excluding social contribution).
Source : Revenus et patrimoine des ménages, Édition 2021.

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 quintiles (Q1 to Q4). Our MPC distribution falls within the lower bounds of Boehm, Fize and Jaravel (2025) using bank data in France.

Figure 14: Wealth inequalities and MPC heterogeneity



Notes: Panel *a*: net mean wealth by net wealth quintile. Panel *b*: instantaneous MPC (total expenditure) by quartile of disposable income.
Sources: Panel *a*: Insee Revenus et patrimoine des ménages, 2021. Panel *b*: Boehm, Fize and Jaravel (2025).

D Additional results – Section 4

In Figure 15, we decompose the welfare effect of τ^h and τ^f into the 5 variables that affect directly households' budget constraint: wages (w), household carbon tax (τ^h), electricity price (p^N), interest rate (R) and housing rents (p^H). To obtain this decomposition, we start from the transition path, and we shut one variable at a time by setting its value to the 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 15: Decomposition of the welfare effect

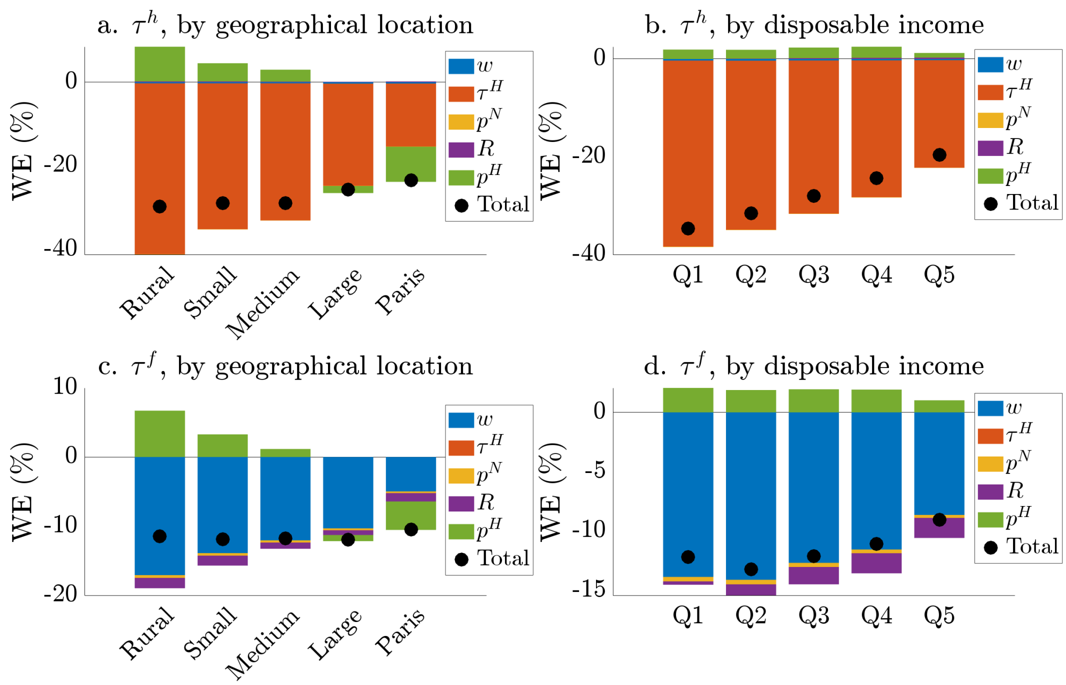


Figure 16 is the same decomposition, but considering only the welfare changes during the first 5 periods of the transition.

Figure 16: Decomposition of the welfare effect at horizon $t = 5$

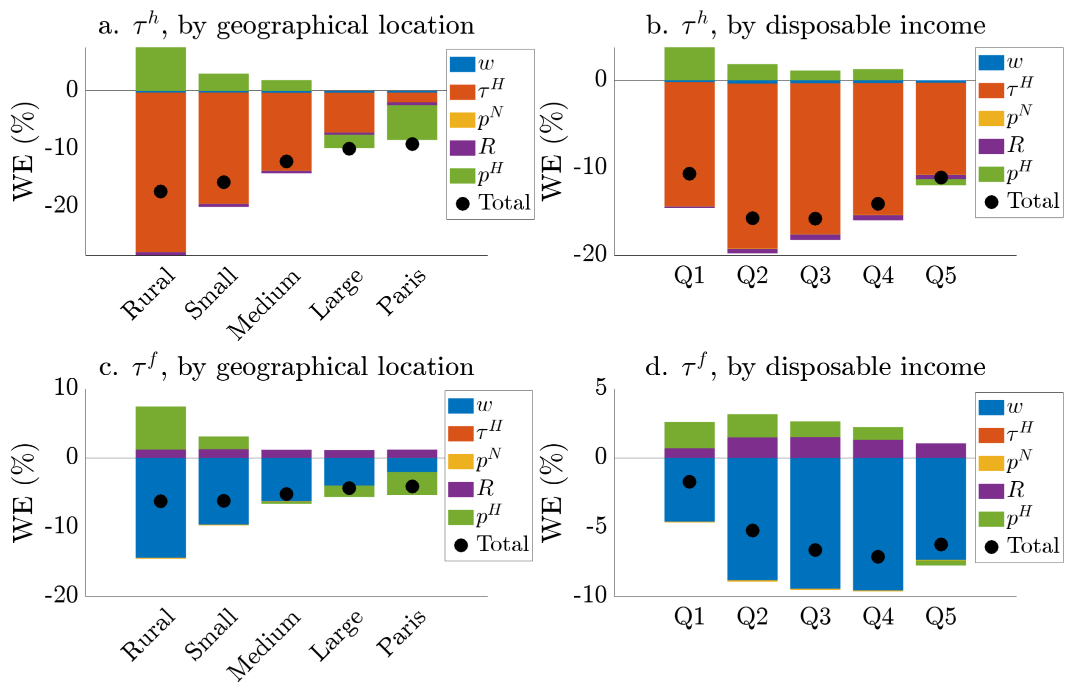
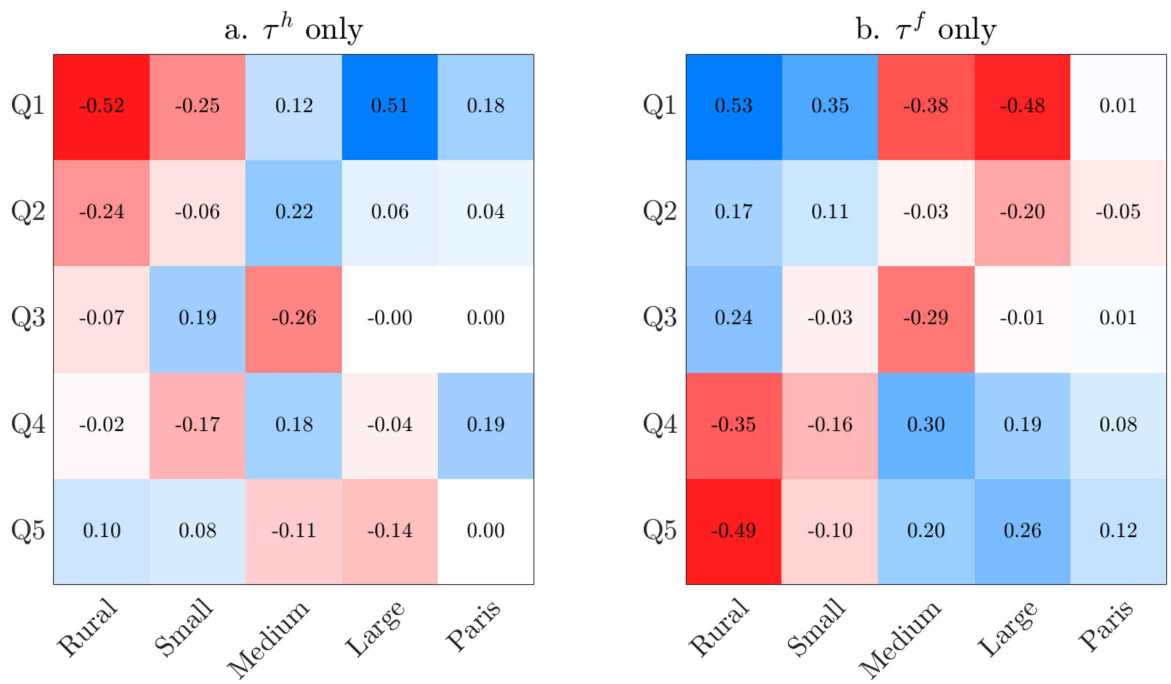


Figure 17 shows, for each group area × income quintile, the change in population between the two steady states. The weighted sum of each line is equal to 0, as the share of households in each disposable income quintile is always 20% but the share of households within each region is not; the sum of each column can be different from 0, as households migrate between regions.

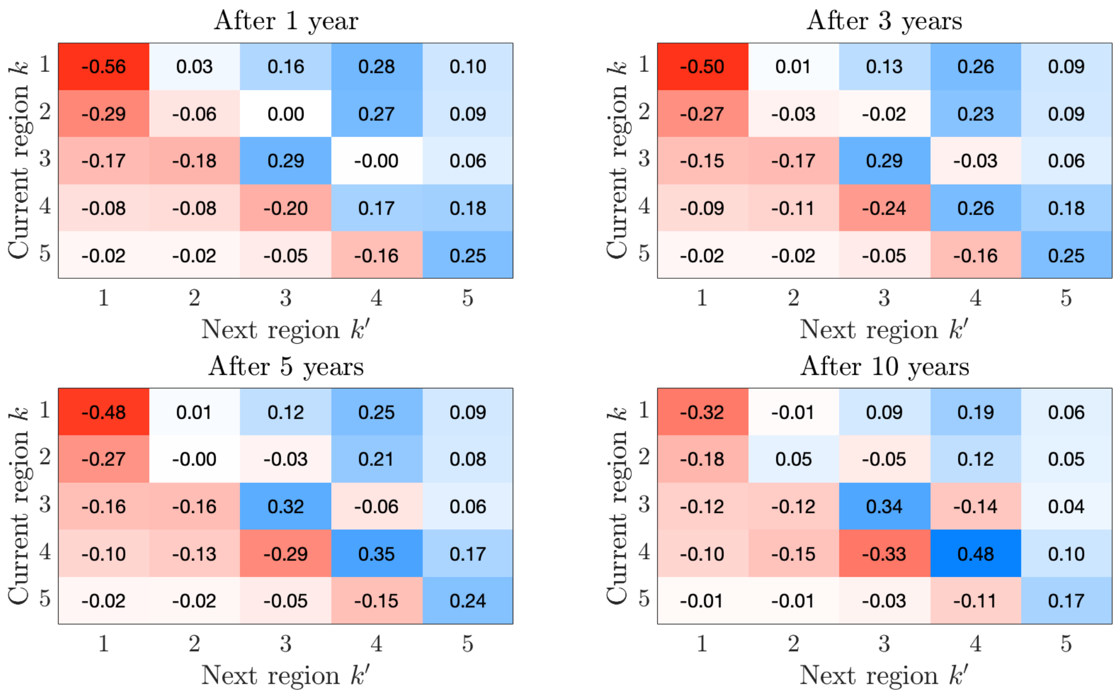
Figure 17: Density change by income and region between steady states



Notes: Panel *a*: only increase τ^h with a 10% decrease in total emissions. Panel *b*: only increase τ^f with a 10% decrease in total emissions. Disposable income quintiles are built at the national level.
Lecture: After the increase in τ^h, in the new steady state, the share of households that are in rural areas and in the 1st quintile decreases by 0.52 points compared to the initial steady state.

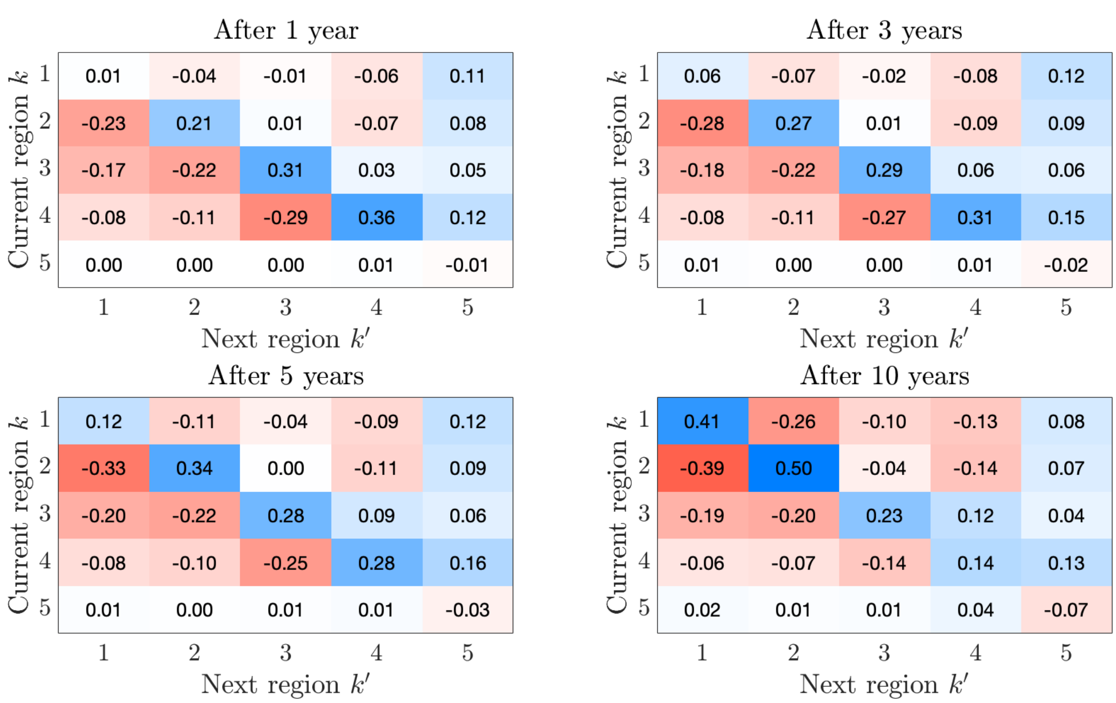
For τ^h, poor households migrate from rural areas to large cities and Paris, due to the direct effect of carbon tax. For τ^f, it is the opposite; rich households migrate to large cities due to the decrease in wage, and poor households move to rural areas due to the decrease in housing rents.

Figure 18: Mobility changes at different time horizon, τ^h only



Lecture: One year after the increase in τ^h, the share of rural households that decide to stay in rural areas (region 1) decrease by 0.56 points compared to the initial mobility matrix.

Figure 19: Mobility changes at different time horizon, τ^f only



Lecture: One year after the increase in τ^f, the share of rural households that decide to stay in rural areas (region 1) decrease by 0.01 points compared to the initial mobility matrix.

E Additional results – Section 5

E.1 τ^h vs τ^f

In Table 11, we show the optimal values of τ^h and τ^f required to reduce emissions by 10%.[17] In the benchmark complete model 1, taxing households is costly in terms of welfare and inefficient at reducing emissions due to the incompressible energy consumption $\bar{e}$. Therefore, the optimal tax is significantly higher for firms than for households. If we remove the geographic dimension from our model by setting $\bar{e}_k$, γ_k, ω_k, and z_k to their average values across all regions, the optimal τ^h increases while τ^f decreases, as households become less constrained. Finally, eliminating non-homothetic preferences by assuming $\epsilon_E = \epsilon_H = 1$ further equalizes the two carbon taxes. Since energy is a necessary good, taxing household energy disproportionately affects poorer households, which have the highest marginal utility. Removing non-homotheticity smooths the carbon tax burden across income groups, thereby reducing the welfare cost associated with τ^h.

Table 11: Optimal taxes to reduce emissions by 10%

Model	**Description**	τ_h	τ_f	Ratio
(1)	Benchmark model	0.045	1.076	0.042
(2)	No geography	0.132	0.743	0.178
(3)	Homothetic preferences	0.334	0.476	0.702

E.2 Recycling policies: additional results

While Table 2 in main test shows the median welfare for each group and each scenario, Table 12 below is the average welfare, computed as the average wealth equivalent (in % of households expenditures) over the transition.

[17] For a comparison, when $\tau_h = \tau_f$ we get $\tau = 0.155$. When adjusting only one tax we get: $\tau_h = 0.587$ and $\tau_f = 0.446$.

Table 12: Average welfare change by location and income

	Scenario	Rural	Small	Medium	Large	Paris	All
(1)	Benchmark model: G	−17.4	−17.3	−16.1	−15.9	−14.7	−16.5
(2)	Uniform transfers	9.1	9.3	8.9	10.0	9.6	9.3
(3)	Income rule	39.5	34.9	18.7	17.9	17.2	27.7
(4)	Geo X Income	32.1	29.7	31.9	32.7	22.8	29.8
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**
(1)	Benchmark model: G	−18.6	−18.8	−17.1	−15.3	−12.5	−16.5
(2)	Uniform transfers	21.9	13.0	7.3	3.5	1.2	9.3
(3)	Income rule	98.9	32.3	6.9	−0.3	0.9	27.7
(4)	Geo X Income	104.4	35.3	8.0	0.5	1.4	29.8

Notes: This represents the average welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different rebating policies.

In Table 13, we show the share of losers by location and by income group, *i.e.* the percentage of households within each group that suffer welfare losses after the policy.

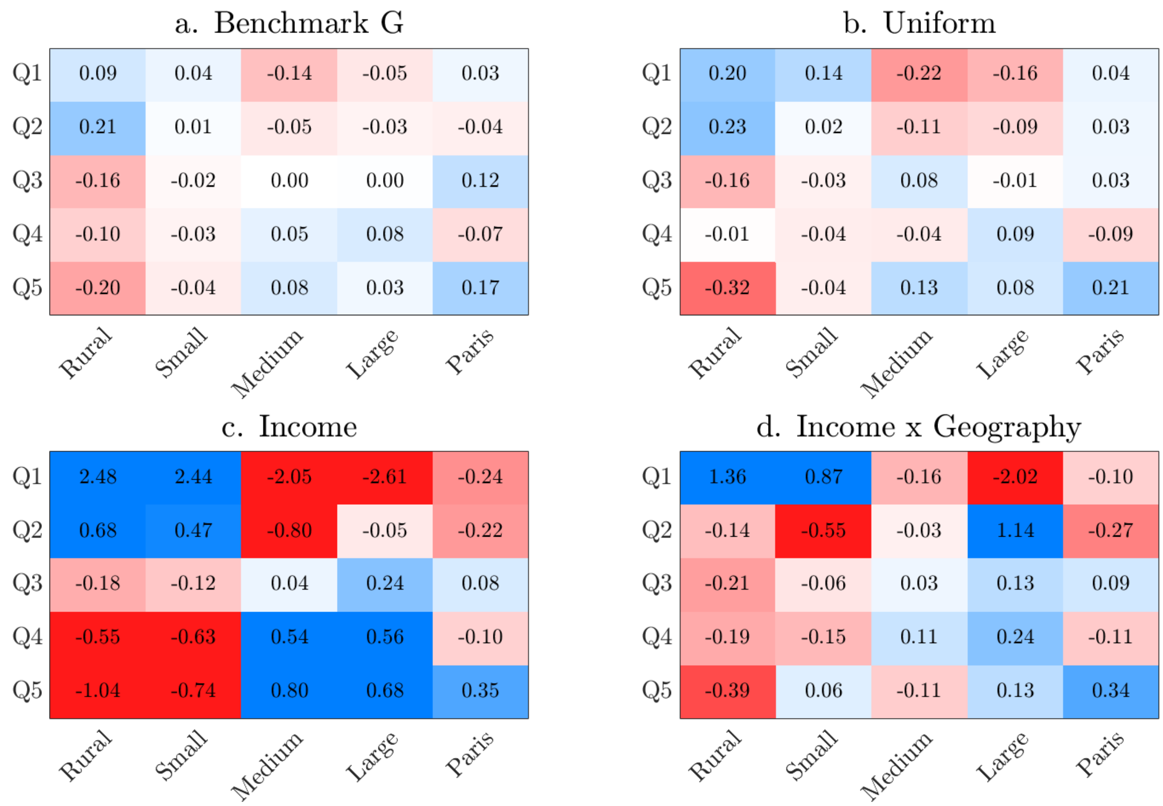
Table 13: Share of losers by location and income

	Model	Rural	Small	Medium	Large	Paris	All
(1)	Benchmark model: G	100	100	100	100	100	100
(2)	Uniform transfers	0	0	0	0	0	0
(3)	Income rule	29.0	27.2	29.3	26.9	6.1	24.2
(4)	Geo X Income	28.2	25.8	25.6	19.9	5.6	21.9
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**
(1)	Benchmark model: G	100	100	100	100	100	100
(2)	Uniform transfers	0	0	0	0	0	0
(3)	Income rule	0	0	6.3	49.6	10.1	24.2
(4)	Geo X Income	0	0	0	49.6	9.5	21.9

E.3 Migration & Transfers

In Figure 20, we show the density change between steady states, for each transfer rule. The "Income" transfer scenario implies large migrations, as poor households are less constrained and can afford to live in rural areas even with high energy requirements. The "Income × Geography" scenario implies fewer migrations, as rich households in rural areas receive a transfer and therefore do not choose to migrate.

Figure 20: Migration dynamics



Notes: Density change by income and region between steady states. Panel a: increase in public spending. Panel b: uniform transfers. Panel c: optimal income rebating rule. Panel d: optimal income $\times$ geography rebating rule.

Lecture: After the scenario "Benchmark G", the share of households that are in rural areas and in the 1st quintile increases by 0.09 points compared to the initial steady state.

E.4 Alternative Pareto Weight

In the main text, we compute the optimal transfer rule by maximizing the welfare using uniform weights. This means we maximize

$$\mathbb{W} = \int_0^1 \alpha_i \sum_{t=0}^{\infty} \beta^t \mathbb{E}_0[U_{i,t}] \mathrm{d}i$$

with $\alpha_i = 1$. In the following Table 14, we use Negishi weights to neutralize the redistribution motive:

$$\alpha_i = \left[\frac{\partial V(a,z,k)}{\partial a}\right]^{-1}$$

The optimal coefficient to maximize welfare with Negishi weights is equal to $x = 1.68$ for the "**Income**" transfer rule (compared to $x = 2.15$ for uniform weights), and $x_k = [2.0, 2.0, 2.25, 2.3, 2.15]$ for the "**Income** $\times$ **Geography**" rule (compared to

$x_k = [2.07, 2.08, 2.38, 2.4, 2.27]$ for uniform weights). Therefore, Negishi weights imply a lower progressivity for the transfer rule, as it neutralizes the redistribution motive. However, as carbon tax is regressive, we still obtain that the optimal transfer is progressive. The average welfare with Negishi-optimal transfer rules are shown in Table 14:

Table 14: Average welfare change by location and income, Negishi weights

	Scenario	Rural	Small	Medium	Large	Paris	All
(1)	Income	33.7	31.0	19.9	20.3	18.8	26.0
(2)	Income × Geography	32.8	29.7	29.6	32.3	21.8	29.4
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**
(1)	Income	87.3	31.8	8.9	1.3	1.2	26.0
(2)	Income × Geography	102.0	34.9	8.2	0.6	1.4	29.4

Notes: This represents the average welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different rebating policies.

E.5 Alternative transfer rule

Our transfer rule from Section 5 is a simple inverse function. In this section, we compute the same results with an alternative formula taken from Ferriere, Grübener, et al. (2023):

$$T(y, \bar{y}) = m\bar{y}\frac{2\exp\left(-\xi\left(\frac{y}{\bar{y}}\right)\right)}{1+\exp\left(-\xi\left(\frac{y}{\bar{y}}\right)\right)} \tag{7}$$

with y total disposable income and $\bar{y}$ mean total disposable income. This transfer function is governed by two parameters: a level m and a phase-out ξ. The parameter ξ determines how quickly transfers phase out with total income. Optimizing our model with this new transfer rule, we get: $m = 0.19$ and $\xi = 6.39$. Figure 21 compares our optimal inverse-rule formula with the transfer rule 7. The rule 21 is more progressive than the main inverse rule, since it fades away faster to 0 when income increases. This additional progressivity allows to reach higher aggregate welfare (around +3% in all scenarios) – see our results of aggregate welfare by income and city-type groups in Table 15. With this transfer rule, we again find that allowing for spatial specific progressivity parameters ξ_k[18] enhances aggregate welfare by +8.3%.

[18]Optimizing other this new set of parameters we get: $\xi_k = [7.69, 7.69, 6.24, 6.08, 6.76]$ and $m_k = 0.19$

Figure 21: Inverse formula vs. formula 7

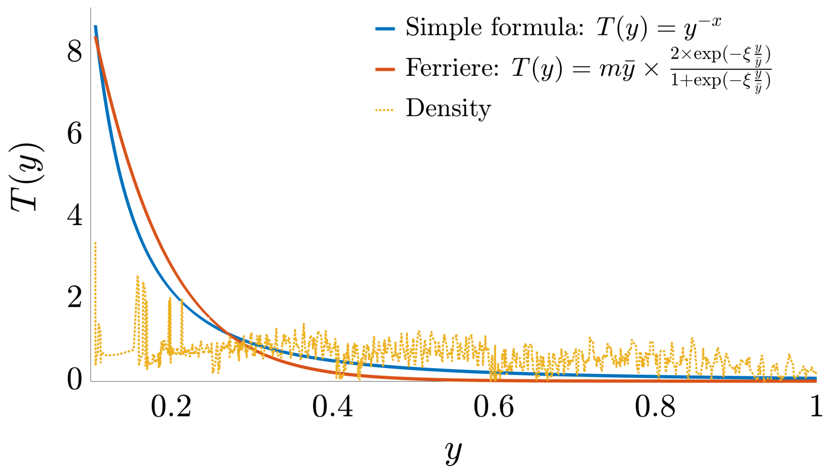


Table 15: Average welfare change by location and income, alternative transfer rule

	Scenario	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**All**
(1)	Income	38.6	36.2	24.2	23.6	21.8	30.3
(2)	Income × Geography	34.7	32.3	34.3	36.6	24.8	32.5
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**
(2)	Income	109.4	36.5	6.7	−1.3	0.8	30.3
(2)	Income × Geography	117.7	38.4	6.5	−1.1	1.3	32.5

Notes: This represents the average welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different rebating policies.

F Robustness

F.1 Elasticities of substitution

Benchmark values for our main elasticities are: $\sigma = 0.2$, $\epsilon_h = 1.5$, $\sigma_y = 0.05$, $\epsilon_y = 1.5$, $\delta_H = 0.2$. In this section, we run the same scenario as our "**Benchmark *G***" for the following alternative values: $\sigma = 0.4$, $\epsilon_h = 1.3$, $\sigma_y = 0.2$, $\epsilon_y = 1.3$, $\delta_H = 0.3$. For each specification, we find the new initial steady state with carbon taxes equal to 0, then the new final steady state with -10% decrease in total emissions. We finally compute the transitional dynamics between the two steady states, to compute average welfare effects (defined as wealth equivalent in percentage of households expenditures) by location and income groups. We present our results in Table 16, where the last column is our inequality ratio, defined as the percentage change between the first and the fifth column (for example, the 18.3% at the first line means that Rural households suffer a welfare loss 18.3% higher than Parisian households).

Table 16: Average welfare change by location and income, different elasticities

	Scenario	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**All**	**Rural/Paris**
(1)	Benchmark model: G	−17.4	−17.3	−16.1	−15.9	−14.7	−16.5	18.3
(2)	$\sigma = 0.4$	−8.8	−8.9	−8.5	−8.2	−8.1	−8.5	8.6
(3)	$\epsilon_h = 1.3$	−20.9	−20.8	−19.1	−18.9	−17.6	−19.7	18.8
(4)	$\sigma_y = 0.2$	−15.8	−15.8	−14.7	−14.5	−13.4	−15.0	17.9
(5)	$\epsilon_y = 1.3$	−19.7	−19.6	−18.1	−17.9	−16.6	−18.6	18.7
(6)	$\delta_H = 0.3$	−17.6	−17.5	−16.2	−16.0	−14.5	−16.6	21.4
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**	**Q1/Q5**
(1)	Benchmark model: G	−18.7	−18.8	−17.1	−15.2	−12.5	−16.5	49.6
(2)	$\sigma = 0.4$	−9.1	−9.5	−8.8	−8.1	−7.3	−8.5	24.7
(3)	$\epsilon_h = 1.3$	−22.0	−22.5	−20.5	−18.4	−15.1	−19.7	45.7
(4)	$\sigma_y = 0.2$	−16.9	−17.1	−15.6	−13.9	−11.5	−15.0	47.0
(5)	$\epsilon_y = 1.3$	−20.8	−21.2	−19.3	−17.3	−14.3	−18.6	45.4
(6)	$\delta_H = 0.3$	−19.0	−19.0	−17.2	−15.3	−12.5	−16.6	52.0

Notes: This represents the average welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different rebating policies. Last column: inequality ratio, defined as the percentage change between the first and the fifth column.

Elasticity of substitution between G&S consumption and energy ($\sigma = 0.4$). Increasing σ substantially reduces welfare losses across all groups. For example, rural welfare losses decline to -8.8% and the Q1 group's losses drop to -9.1%. This is because households adapt more easily to higher fossil fuel prices. Note that this also dampens both geographic and income-based inequalities in welfare impacts: the rural-to-Paris welfare gap decreases from 18.3% in the benchmark to 8.6%, and the Q1-to-Q5 gap drops from 49.6% to 24.7%.

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 -20.9% and Q1 losses increase -22.0%. The rural-to-Paris welfare gap widens slightly to 18.8%, while the Q1-to-Q5 gap narrows modestly to 45.7%.

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 (-15.8) and poor (-16.9) households. The rural-to-Paris welfare gap decreases slightly to 17.9%, and the Q1-to-Q5 gap narrows to 47.0%. This indicates that greater substitution flexibility in production not only lowers overall welfare costs but also marginally reduces income and geographic disparities.

Elasticity of substitution between fossil fuels and electricity for firms ($\epsilon_y = 1.3$). Decreasing ϵ_y from 1.5 to 1.3 increases welfare losses across all groups, as energy is less substitutable, creating a higher decline in wages and interest rate. Rural areas face a loss of -19.7 while Q1 losses increase to -20.8. The rural-to-Paris welfare gap widens slightly to 18.7% while the Q1-to-Q5 gap narrows modestly to 45.4%.

Elasticity of housing supply ($\delta_H = 0.3$). Increasing δ_H does not change aggregate losses (-16.5 against -16.6) but it amplifies distributive effects. The rural-to-Paris welfare gap increases significantly to 21.4%, while the Q1-to-Q5 gap widens to 52.0%. These results suggest that more elastic housing supply amplifies both income and spatial disparities in welfare costs.

F.2 Partial Equilibrium vs General Equilibrium

Most of the empirical literature on the distributive effects of carbon taxes imputes emissions to households' consumption basket, either directly (on direct consumption of fossil fuels) and indirectly (on imputed carbon content of good and services). In this section, we run a "partial equilibrium" analysis in our model. We take as given all the prices and the distribution, and we impute emissions to F^h and c, knowing that F^h accounts for 40% of national emissions and therefore c should account for 60%. Finally, we find the carbon tax τ such that emissions are reduced by 10%, assuming F^h and c are taxed proportionally to their emission intensity. Table 17 shows the median welfare, computed as wealth equivalent, between our benchmark model (general equilibrium) and this partial simulation.

Table 17: Median welfare change by location and income

	Scenario	Rural	Small	Medium	Large	Paris	Rural/Paris
(1)	General equilibrium	−17.4	−17.3	−16.1	−15.9	−14.7	18.3
(2)	Partial equilibrium	−87.7	−83.2	−68.9	−68.8	−69.6	26.0
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1/Q5**
(1)	General equilibrium	−18.7	−18.8	−17.1	−15.2	−12.5	49.6
(2)	Partial equilibrium	−78.6	−82.6	−84.7	−74.8	−63.7	23.4

Notes: This represents the median welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different rebating policies. Last column: inequality ratio, defined as the percentage change between the first and the fifth column.

The welfare cost is significantly higher in partial equilibrium because households must fully bear the tax burden through changes in expenditures, without adjustments in wages, rents, or interest rates. While τ^h allows households to substitute towards c and N, and τ^f enables firms to substitute toward capital and labor, this unique τ restricts households' ability to adjust, forcing a reduction in their overall consumption basket. In partial equilibrium, households decrease their consumption of goods (−5.4%) and fossil fuels (−16.9%) while increasing electricity consumption (+22.3%). Because we assume a fixed population density, migration is not an option, further amplifying the tax burden. Consequently, partial equilibrium analysis overstates spatial effects compared to our general equilibrium framework.

On the opposite, partial equilibrium underestimates the income dimension. τ^h is regressive because it disproportionately affects households with high fossil fuel consumption, and τ^f is regressive through its negative impact on wages. In partial equilibrium, our τ does not affect wages, and targets consumption c and not only fossil fuel F^h, leading to a more balanced distributional impact across income groups.

F.3 Endogenous fossil fuel price

In this section, 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. We consider two cases: $\delta_F = 0.1$ and $\delta_F = 0.5$. For both cases, we calculate the transition dynamics using the same carbon tax increase as in our Benchmark G scenario from Section 5. In these new scenarios, total emissions decrease by 9.6% when $\delta_F = 0.1$ and by 8.3% when $\delta_F = 0.5$. Welfare results, broken down by location and income groups, are reported in Table 18. These adjustments do not alter our overall quantitative findings.

Table 18: Average welfare change by location and income, p^F endogenous

	Scenario	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**All**	**Rural/Paris**
(1)	Benchmark model: G	-17.4	-17.3	-16.1	-15.9	-14.7	-16.5	18.3
(2)	$\delta_F = 0.1$	-16.7	-16.6	-15.4	-15.2	-14.0	-15.8	19.3
(3)	$\delta_F = 0.5$	-14.3	-14.2	-13.2	-13.1	-12.0	-13.5	19.2
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**All**	**Q1/Q5**
(1)	Benchmark model: G	-18.7	-18.8	-17.1	-15.2	-12.5	-16.5	49.6
(2)	$\delta_F = 0.1$	-17.8	-18.0	-16.4	-14.6	-12.0	-15.8	48.3
(3)	$\delta_F = 0.5$	-15.3	-15.4	-14.0	-12.5	-10.3	-13.5	48.5

Notes: This represents the average welfare change (one-time wealth-equivalent transfer expressed in % of households' disposable income) for each group over the transition, for different rebating policies. Last column: inequality ratio, defined as the percentage change between the first and the fifth column.