Geography versus Income: The Heterogeneous Effects of Carbon Taxation

Charles Labrousse* and Yann Perdereau†

March 7, 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 2.7 times more on fossil fuels than urban households and are employed in firms that emit 3 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. We find that rural households experience 20% higher welfare losses, and failing to account for geography in optimal revenue recycling lowers aggregate welfare by 7%.

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, François Langot, Matthieu Lequien, 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 in firms' input costs in rural areas. These distributive effects can undermine the political acceptability of carbon taxation, as illustrated in France with 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 existing literature has predominantly focused on the "rich versus poor" dimension of the energy transition burden, less attention has been given to the specific role of geographical heterogeneity in energy consumption and emissions patterns. This paper addresses this gap by providing detailed empirical evidence on regional disparities and integrating these patterns into a rich quantitative model.

Using several datasets covering the French economy, we systematically document the distribution of direct emissions across both households and firms. We link household-level surveys to fiscal declarations to estimate fossil fuel consumption for heating and transportation at a highly granular level. Worker-level emission patterns are derived from matched employer-employee administrative data combined with firm-level emissions. Our findings reveal that rural households bear a dual burden under carbon taxation. They have greater energy needs for both transportation and heating, unlike urban households, which benefit from accessible public transit and smaller, more energy-efficient homes. Furthermore, carbon-intensive industries, such as agriculture and metallurgy, tend to cluster in rural areas, while urban workers are more frequently employed in less carbon-intensive service sectors.

We then integrate these emission patterns into a new spatial heterogeneous-agent model that captures heterogeneity in both income and geography, allowing us to explore their implications for the distributive effects of carbon taxation. To our knowledge, this is the first model to simultaneously incorporate endogenous savings and migration choices within a fully-fledged heterogeneous-agent general equilibrium framework. Consistent with microdata, each region in the model is characterized by specific energy expenditure shares for both households and firms, and housing and labor markets are segmented in each area. Households endogenously choose whether to migrate in response to regional differences in carbon taxation, capturing mobility frictions and relocation incentives. Our model successfully replicates observed heterogeneity in income, wealth, and energy consumption across regions, as well as the cross-correlation between income, geography, and migration patterns. We then introduce carbon taxes on both households and firms and evaluate a range of revenue-recycling scenarios, from increased public spending to targeted transfers based on location and income. Under a welfare-maximizing planner with an emissions constraint, we investigate optimal revenue-recycling policies and the resulting political economy implications. Our paper yields three key findings.

First, using micro data on households and firms, we show that **geography is more important than income to assess emission patterns**. Our analysis of household-level survey data reveals that rural households consume 2.7 times more fossil fuels, primarily due to larger homes and higher reliance on car travel. Notably, supplementary 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, or the Netherlands. Moreover, our matched employer-employee dataset indicates that rural workers are twice as likely as their urban counterparts to be employed in emission-intensive sectors, such as agriculture and manufacturing. By attributing firm-level emissions to employees based on firm size and sectoral emission intensity, we find that rural households are employed in firms emitting three times more greenhouse gases than those employing Parisian households. These findings are embedded 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 by income, tax type, and time horizon. In our benchmark scenario, targeting a 10% reduction in emissions, median welfare losses in rural areas are 20% higher than those in Paris (−17.3% vs. −14.5%). We decompose these effects across our two tax types: on households' direct emissions and on firms' direct emissions. The tax on household is highly regressive, as energy is a necessity good, disproportionately burdening low-income households. The firm tax is less regressive, as it primarily reduces wages – affecting middle-income households – and lowers interest rates, which impacts 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 attracts them through falling housing prices. Overall, 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.

Third, we find that **ignoring geographical location in recycling rules reduces aggregate welfare by 7%**. In a scenario targeting a 10% reduction in emissions, our optimal recycling policy – targeting 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 cuts the share of households experiencing welfare losses by 10% compared to income-based transfers. A key mechanism is that location-based targeting dampens migration flows, thereby mitigating welfare costs. Importantly, these findings remain robust across alternative welfare objectives, Pareto weights, and parametric formulas.

Our main contribution is to develop a unified framework for analyzing the 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 distribution, typically along the income dimension, to energy prices, which are impacted by carbon taxes. This requires accounting for both the direct effect (households consume energy 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 introduce geographical heterogeneity. Our framework is similar to Känzig (2023), who integrates energy into both household final consumption and firm inputs, capturing distributive effects on both household income and expenditures; we add an additional layer of heterogeneity by considering the spatial dimension. Finally, a central component of the analysis of the distributive effects of carbon taxation is the use of carbon tax revenue. As in Goulder et al. (2019) and Mathur and Morris (2014), we demonstrate that transfers improve welfare and can make the policy progressive when targeted at low-income households. However, we find that income-based transfers do not fully compensate individuals in rural areas, motivating the exploration of geography-based transfers. Unlike Fried, Novan and Peterman (2024) and Barrage (2020), who consider reducing existing distortionary taxes, we focus on transfers, as they explicitly separate carbon tax revenue from the general state budget, thus enhancing the political acceptability of the policy.

This paper also contributes to the *macroeconomic literature on heterogeneity* by introducing a spatial dimension into heterogeneous-agent models. We start with the Aiyagari (1994) model, with idiosyncratic productivity shocks that generate an endogenous income and wealth distributions. We extend this framework by introducing non-homothetic preferences, as in Comin, Lashkari and Mestieri (2021), to model household energy demand, and by incorporating multiple production sectors, following Barrage (2020), to capture firms' energy demand. We also allow for substitution between clean and dirty energy using CES energy baskets. Since geography is a key dimension of heterogeneity (see Redding and Rossi-Hansberg (2017)), our contribution is to add a geographic layer to this framework while preserving the rich general equilibrium structure of heterogeneous-agent models. Specifically, we incorporate endogenous migration, city-specific income levels, energy requirements, and segmented housing and labor markets. Following Fajgelbaum et al. (2019), who examine location choices in response to state taxes in the U.S., and Desmet and Rossi-Hansberg (2014), who study sectoral recomposition across regions, we highlight the key role of worker reallocation in shaping the distributive effects of carbon taxation. Households are modeled with discrete location choices, subject to a monetary migration cost, if their expected lifetime utility is higher in another region. Following Couture et al. (2024), Kleinman, Liu and Redding (2023) and Franklin et al. (2024), households draw preference shocks from an extreme-value distribution, preventing concentration of rich or poor households in a single region. We extend this static framework by introducing endogenous wealth accumulation, enabling households to save and finance migration. Given that we study a permanent increase in carbon taxes leading to a new steady state, we account for endogenous population dynamics, as emphasized by Hurst et al. (2016). Our calibrated model replicates the observed joint distribution of household income and geography, influenced by city-specific wages and housing prices, as in Allen and Arkolakis (2014) and Davis and Dingel (2019). However, we depart from their assumption of symmetric fundamentals by allowing for region-specific energy requirements. In doing so, our model bridges the gap between heterogeneous-agent macroeconomic models and spatial frameworks with endogenous migration. Closest to us, Bilal and Rossi-Hansberg (2021) proposes a dynamic location model with both endogenous mobility choices and wealth accumulation. They focus on the individual choice between savings and mobility decisions following income shocks in a partial equilibrium framework. We expand their set-up in a general equilibrium model.

The remainder of the paper is organized as follows. Section 1 presents descriptive evidence on the distribution of households' and firms' direct emissions. 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 explores optimal carbon taxes and revenue-recycling policies. Finally, Section 6 concludes.

1 Descriptive Evidence

This section presents descriptive evidence on the distribution of direct 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, firms in rural areas tend to concentrate in more emission-intensive sectors. 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,[1] 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 for more then 97% of households' direct emissions, other activities being unidentified in consumption surveys. We then consider total energy consumption as the sum of fossil fuel expenditures and total electricity expenditures.[2] Throughout the paper, we classify locations into five city types: Rural, Small cities, Medium cities, Large cities, and Paris, based on population size.[3] These categories represent 23.5%, 26.0%, 18.5%, 13.4%,

[1]This survey is used to build consumption baskets for the French CPI and the Harmonised Index of Consumer Prices (HICP) used by the ECB.

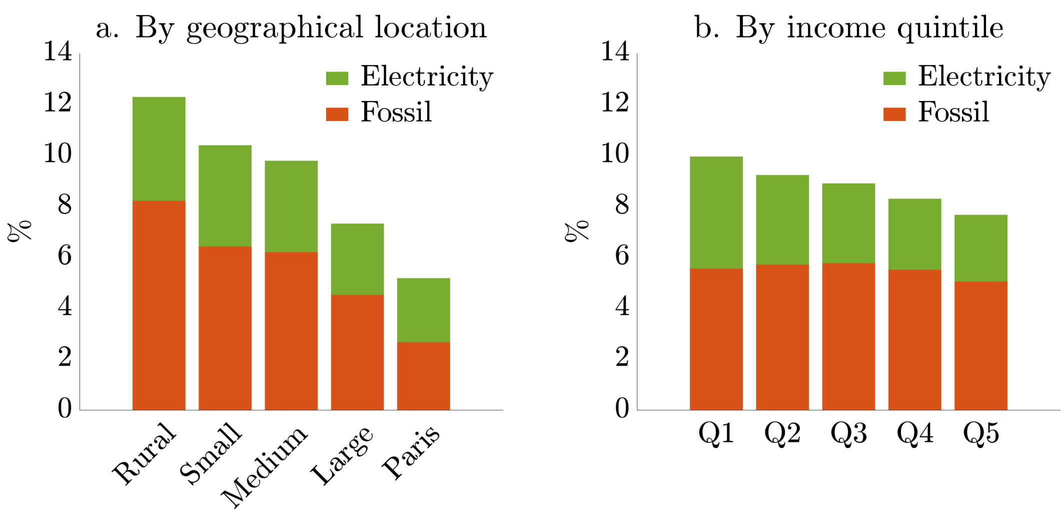
[2]In the BdF survey, as in the US Consumer Expenditure Survey, it is not possible to distinguish between electricity expenditures for housing purposes and those for charging car batteries.

[3]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

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 accounts for any 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. While total energy is a necessary good—its share decreases from 10% for the first income quintile (Q1) to 8% for the fifth quintile (Q5)—the fossil fuel share remains flat across the income distribution, at approximately 5.5% of total expenditures. In contrast, geography strongly predicts energy consumption: rural households consume 2.1 times more energy than Parisians (12.1% versus 5.7%) and 2.7 times more fossil fuels (8.1% versus 3%). We then impute the fossil fuel share for all households in France using the complete set of fiscal declarations from households in 2021.[4] We present its spatial distribution in Figure 3, by averaging fossil fuel shares at the thinner geographical code available.

Figure 1: Energy share in total consumption



Note: share of fossil fuel and electricity in total consumption expenditures, controlling for variables detailed in Appendix A.4.

To explain these differences in energy shares, we decompose household energy use into *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: 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

map of France corresponding to these categories.

[4]See Appendix A for details.

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[5] also reveals that rural households have nearly twice the living space of Parisian households—an average of 105.6 square meters compared to 64 square meters in Paris. When examining 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 fewer cars. The number of vehicles and the necessity of commuting increase with income, resulting in relatively flat 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.

[5]Supplementary data is available in Appendix A.

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 generalizes 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/Q5 ratios of 1.1, 1.1, 0.7, and 1.0, respectively. However, the energy share in these countries varies significantly by living area, with Rural/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). However, 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 lower-income households allocate a substantial share of their expenditures to transportation.

Therefore, **geography plays a more significant role than income in explain-**

ing 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 account for the majority of direct emissions from households. 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, are more emissions-intensive than others and, therefore, more affected by carbon taxes. Moreover, these sectors are unevenly distributed across regions and occupations, meaning that both income and geography influence the firms in which 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 DADS.[6] The DADS dataset has two advantages. First, it is highly representative, containing more than 3 million individuals in each cross-section. Second, it is a panel dataset that covers the entire work history of individuals, providing rich demographic, geographic, and firm-level information.[7] The large sample size enables us to conduct a detailed analysis by city code and to finely disaggregate employer and worker groups, which allows for controlling composition effects. Our contribution is to merge this dataset with sectoral emissions data from CITEPA and official government reports.[8]

The methodology is as follows: using sectoral-level emission intensity (in equivalent tCO_2 per euro of value-added), firm size and the firm in which households are employed in 2021,[9] we impute firm-level emissions to its workers. This results in a metric of "tons of CO_2eq per worker", which does not represent individual emissions or the "climate responsibility" of workers. Instead, it serves as a proxy for the potential impact on workers of a carbon tax imposed on the firms they work for.

Empirical results. We regress households' "tons of CO_2eq per worker" on city type, income quintile, as described in Appendix A.4. The predicted tCO_2eq 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.[10] Figure 2 reveals that rural households work in firms that are 3 times more polluting than Parisian households (24 tCO_2 versus 8). Moreover, considering that rural areas account for 24% of the population, compared to

[6]DADS: *Déclarations Annuelles de Données Sociales.*

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

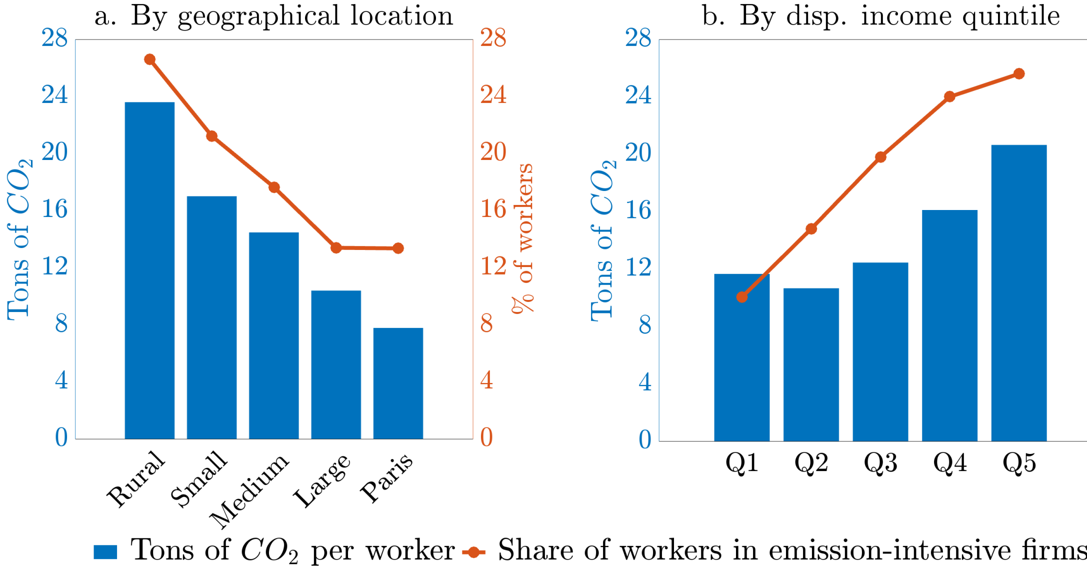
[8]See Appendix A.3 for further details.

[9]This is the most recent DADS cross-section available.

[10]Emissions-intensive sectors are defined as those with a share of total emissions larger than their share of total value-added.

19% for Paris, we find that firms in rural areas contribute to 36% of total firm emissions, versus 9% for Paris. Along the income dimension, wealthier households tend to work in more emissions-intensive firms, but the gradient is less pronounced compared to the spatial dimension.

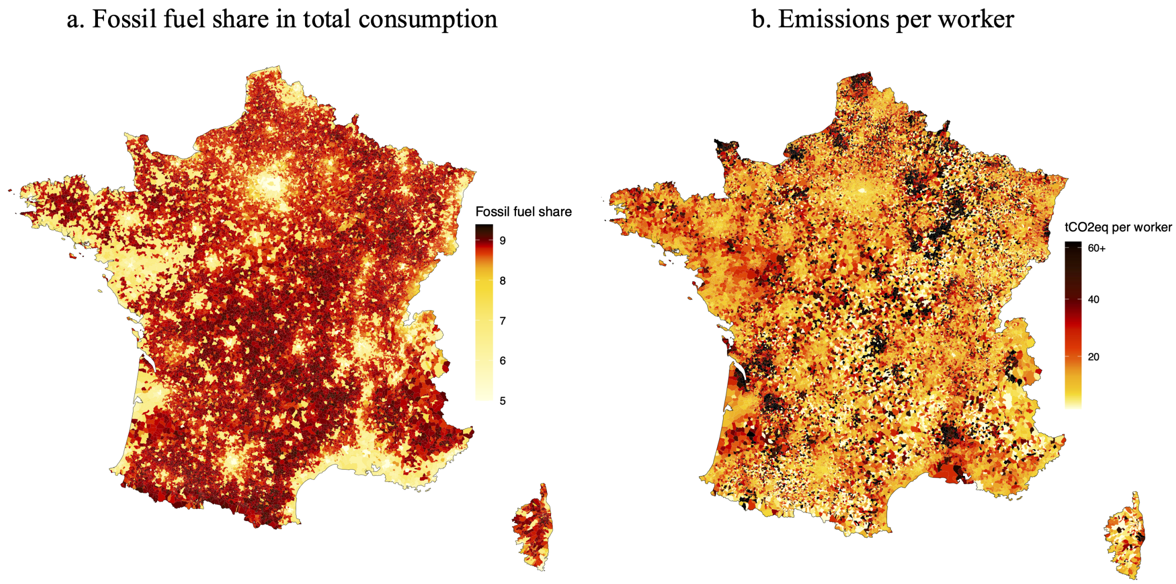
Figure 2: Emissions imputed to workers and share of workers in emission-intensive firms



Note: tons of $C0_2$ imputed per worker, controlling for variables detailed in Appendix A.4.

We provide a sectoral decomposition along the income and geographical dimensions in Table 7 in Appendix to explain these results. The two most polluting sectors, agriculture and industry, are heavily concentrated in rural areas. While 3.1% and 21.2% of rural households are employed in these sectors, only 0.1% and 8.7% of Parisian households work in them. In contrast, 4.9% and 7.4% of high-income households work in agriculture and industry, compared to 2.6% and 5.3% of households in the first income quintile. Therefore, since both rural and wealthier households are more likely to work in emission-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*: CITEPA, national accounts and 2021 DADS.

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 in firms that are more emission-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 households à la Aiyagari (1994), with idiosyncratic productivity shocks leading to income and wealth heterogeneity, and 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 and constituting an independent contribution, 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 may choose to change city type but they incur a fixed monetary migration cost: $\kappa(k, k') \geq 0$. As in Ferriere et al. (2023), 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', 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 problem[11] (omitting subscript i for clarity):

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

subject to:

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

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

[11] Denoting a the assets, z the idiosyncratic productivity, 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.

$$\underbrace{(1+\tau^{\text{VAT}})\left[c_t + p_t^N N_t^h + (p_t^F + \tau_t^h)F_t^h\right] + p^H(k_t)H_t}_{\text{Total consumption expenditures}} + \underbrace{a_{t+1} - a_t}_{\text{Savings}} + \underbrace{\kappa(k_t, k_{t+1})}_{\text{Migration cost}}$$

$$= \underbrace{\Gamma\left(z_t(k_t)w(k_t)\bar{l}\right)}_{\text{Net labor income}} + \underbrace{(1-\tau^k)r_t a_t}_{\text{Net capital income}} + \underbrace{T_t(k_t)}_{\text{Transfers}} \quad (3)$$

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

$$a_t \geq \underline{a} \quad (5)$$

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. 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, that may be contingent to their disposable income level or their living area.

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, which allows us to match the cross-distribution across income and living areas.

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 city-specific to match the fact that carbon-intensive industries are often located in rural areas, compared to less intensive service firms in urban areas. All other parameters $(\delta, \alpha, \sigma_y, \gamma_y, \epsilon_y)$ are similar across cities. Since labor supply is not uniformly distributed, 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 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 lump-sum 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), we have households total aggregation $x_t = \int x \, \mathrm{d}\mu_t(a, z, k)$ 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:

$$\begin{aligned} T_t + G_t + r_t \bar{d} = \int \left[z_{i,t} w_t l_{i,t} - \Gamma(z_{i,t} w_t l_{i,t})\right] \mathrm{d}\mu_t + \tau^k r_t a_t + \tau^{\mathrm{VAT}} \left(c_t + p_t^N N_t^h + p_t^F F_t^h\right) \\ + \underbrace{\tau_t^h (1 + \tau^{\mathrm{VAT}}) F_t^h + \tau_t^f (F_t^y + F_t^N)}_{\text{Carbon tax revenue (CTR)}} \end{aligned}$$

Following Heathcote, Storesletten and Violante (2017), we assume a progressive labor tax of the form:

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

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 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:

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

Households' savings are invested in capital, housing and public debt. Capital depreciates at rate δ, and we assume a mutual fund redistributes the revenue from capital, debt and housing assets to the households, so that the equilibrium condition is true: $r_t a_t = (r_t^K - \delta)K_t + \sum_k p_{k,t}^H H_t^k + r_t d_t$. 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). 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 $\{c_t, e_t^h, H_t, N_t^h, F_t^h, a_{t+1}, k_{t+1}\}_t$, 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 decision $\{N_t, K_t^N, F_t^N\}_t$, relative prices $\{r_t, w_{k,t}, p_t^N\}_{k,t}$, fiscal policies $\{\Gamma(\cdot), \tau^k, \tau^{\mathrm{VAT}}, \tau_t^h, \tau_t^f\}_t$, 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.

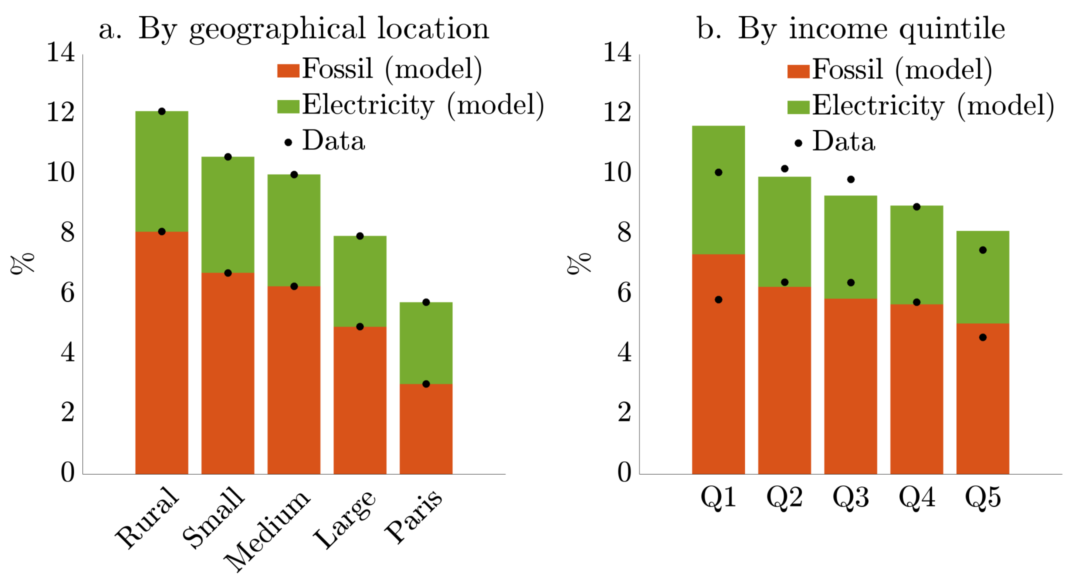
3 Calibration on French macro and micro data

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. 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 income distribution, and ϵ_C is normalized to 1. 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



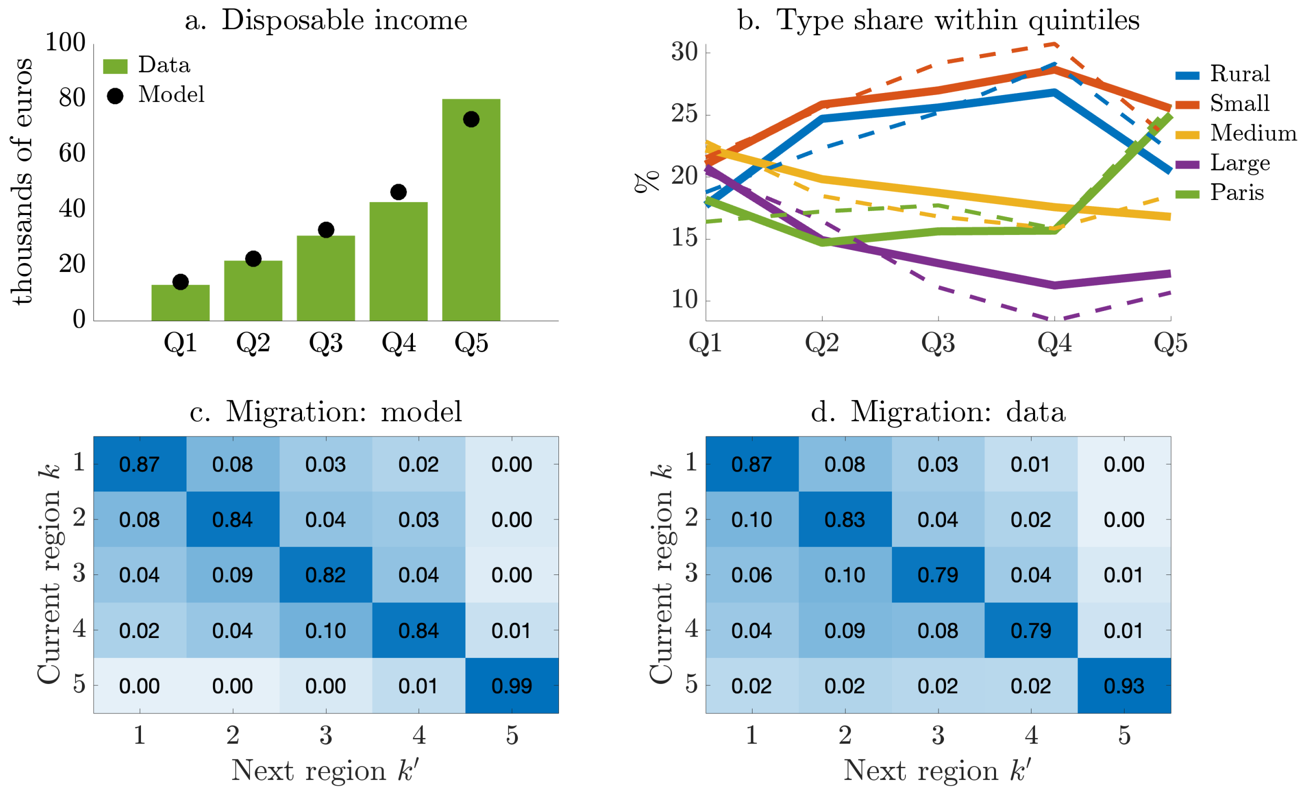
Notes: share of fossil fuel $[(p^F + \tau^h)F^h]$ and electricity $[p^N N^h]$ in total consumption expenditures $[c + (p^F + \tau^h)F^h + p^N N^h]$. Panel *a*: by geographical location. Panel *b*: by disposable income quintile, untargeted.
Source: BdF 2017 Insee survey.

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 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[12] (Figure 5.a), using the AR(1) persistence parameter ρ_z that we set equal for 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, with over-representation in Q2, Q3 and Q4, and under-representation in Q1 and Q5.

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

Figure 5: Distribution of households and migration matrix



Notes: Panel *a*: quintile of disposable income. Panel *b*: share of each geographical location type within each quintile in data (solid lines) and in the model (dashed lines). Panel *c and d*: probability of migrate from k towards k', with $\{1, 2, 3, 4, 5\} = \{\text{Rural, Small, Medium, Large, Paris}\}$.
Sources: Panel *a*: RPM 2021 Insee survey. Panel *b*: BdF 2017 Insee survey. Panel *d*. Constructed using panel data from DADS 2016-2021.

Migration and other parameters: we compute the migration matrix between each region over 5 years[13], *i.e.* the probability of being in region k' at time $t + 5$ when the household is in region k at time t. We create a 5×5 migration cost matrix κ to match this migration matrix, and show our results in Figure 5. We recover the fact that 85% of households on average stay where they are (diagonal of the matrix), that the movers tend to relocate to a close city type (the values around the diagonal), and that Paris constitutes the principal pole of attraction, with a very small probability of leaving. It is not possible to recover perfectly the matrix, because the current migration matrix in the data is not stationary and then does not lead to the current population densities. Finally, we set the annual discount factor $\beta = 0.94$ to match the French

[13] To compute this migration matrix, we use the panel data DADS 2016-2021. We keep only workers between 30 and 55 years old, with annual wage above €2,100, and present in the dataset between 2016 and 2021. This represents 1,010,559 individuals.

capital-to-income ratio[14] when excluding public debt: $\frac{a}{\text{GDP}} = 4.5$. Like in Kaplan, Moll and Violante (2018), we set the intertemporal elasticity of substitution (IES) $1/\theta$ to 1.

3.2 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 lies within the range of estimates from Papageorgiou, Saam and Schulte (2017): we provide robustness check for alternative values in Appendix F. The capital share is set to $\alpha = 0.31$ to match the share of labor revenue $\frac{wl}{\text{GDP}} = 65\%$ following Cette, Koehl and Philippon (2019). The share of fossil fuel in the policy mix is set to $\gamma_y = 0.86$ such that electricity accounts for 33% of the regional firms' energy mix. Finally, the depreciation rate is set to $\delta = 11.8\%$ to match the aggregate share of investment as in Auray et al. (2022).

Electricity firm and other parameters: the electricity sector is capital intensive, so we set $\zeta = 0.9813$ to have $\frac{F_N}{F} = 1\%$. We assume that electricity is produced using few fossil fuel inputs because France relies mainly on nuclear power plants and hydroelectricity from dams. The initial price p^F of the imported fossil fuel is set such that fossil fuel imports account for 4% of the GDP. 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.

3.3 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 11.a. We set the labor tax progressivity to $\tau = 0.08$ following Ferriere et al. (2023). The level of the tax λ is set such that public spending $\bar{G}$ makes 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% following Auray et al. (2022) estimates. The resulting

[14] See 2022 Banque de France report.

amount of tax paid by each households is shown in Figure 11.b. The fit with 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 Section 2 and 3, we build a spatial heterogenous-agent model, calibrated on France. In this Section, we increase carbon taxes τ^h or τ^f and compute welfare change, taking into account transitional dynamics.

Experiment. The experiment is the following. 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} in 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 equivalent along the transition. It answers the question: "in percentage of my income, how much money should I receive at the steady state to be indifferent between staying at the steady state, or going to the transition?". Formally, we compute, for each initial wealth a_0, region k_0 and productivity z_0, the $x(a_0, k_0, z_0)$ in 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 income: $\text{WE}(a_0, k_0, z_0) = x(a_0, k_0, z_0)/\text{TI}(a_0, k_0, z_0)$.[15]

In this section, we describe the transmission of τ^h and τ^f on 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.

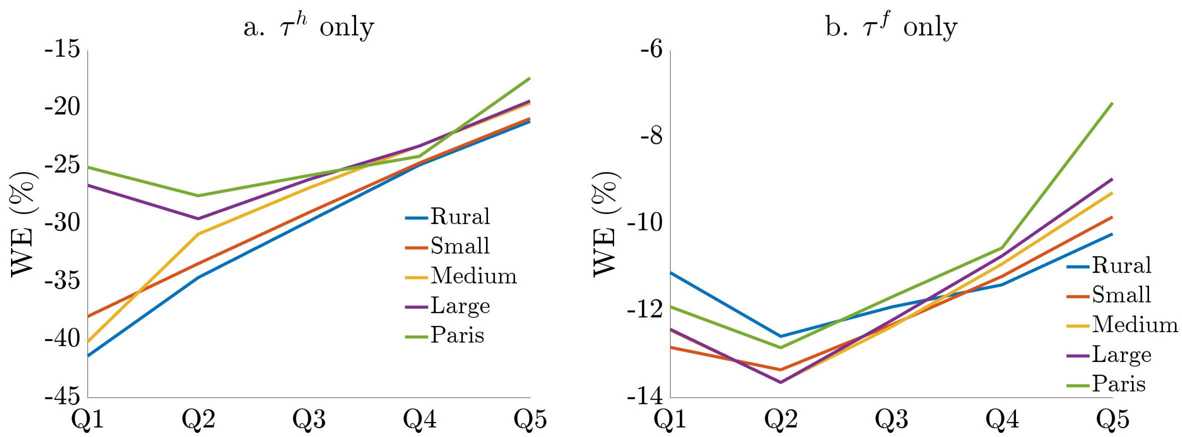
4.1 The distributive effects of carbon taxes

The carbon tax burden varies significantly depending on location, income, and the type of tax. Figure 6 presents the average welfare effects (in wealth equivalent, as described above) by region and income quintile, for τ^h (left panel) and τ^f (right panel).

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

Before examining the different channels, we provide some general observations. First, there is a welfare cost associated with reducing emissions by 10%, as wealth equivalents are negative. This cost is higher for τ^h (-25% on average) than for τ^f (-11%). This implies that the social planner would need to compensate each individual with 9,500€ in Europe (or $15,000$\$ in the US) to make households accept the increase in τ^h (assuming an inefficient rebating policy and no welfare cost from emissions; these points will be discussed in Section 5). Second, both taxes are regressive, as the welfare cost is higher for poorer households. The regressive effect 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 6: Welfare effect by region and income



Carbon tax on households (τ^h): Taxing households' fossil fuel consumption directly affects their consumption baskets without interacting with firms. As shown in the decomposition in Figure 13, the overall welfare impact of τ^h depends on two key factors: the direct effect of the carbon tax and the change in housing prices 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 for goods and fossil fuels for 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 -40% in rural areas compared to -17% in Paris, and -38% for the bottom income quintile (Q1) versus -22% for the top quintile (Q5). However, this adverse effect on rural households is partially offset by a decline in housing prices. As some households migrate from small cities 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 due to differing energy consumption patterns, migration and housing market adjustments alleviate some of this burden.

Carbon tax on firms (τ^f): Taxing firms' fossil fuel consumption alters their input mix and impacts households through changes in income and general equilibrium effects. As illustrated in Figure 13, the welfare impact of τ^f depends on adjustments in wages, housing prices, 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 1.1% in Paris. This results in welfare costs of -17% and -5%, respectively. The decline in wages disproportionately affects lower-income households, as labor income constitutes a larger share of their total income. Similar to τ^h, this geographic burden is partially offset by changes in housing prices: as households migrate from rural areas to urban areas for better wages, p^H decreases in rural areas, generating a welfare gain for households that remain. Lastly, the reduction in firms' capital demand lowers the interest rate, disproportionately affecting wealthier households, as capital income represents a larger share of their income.

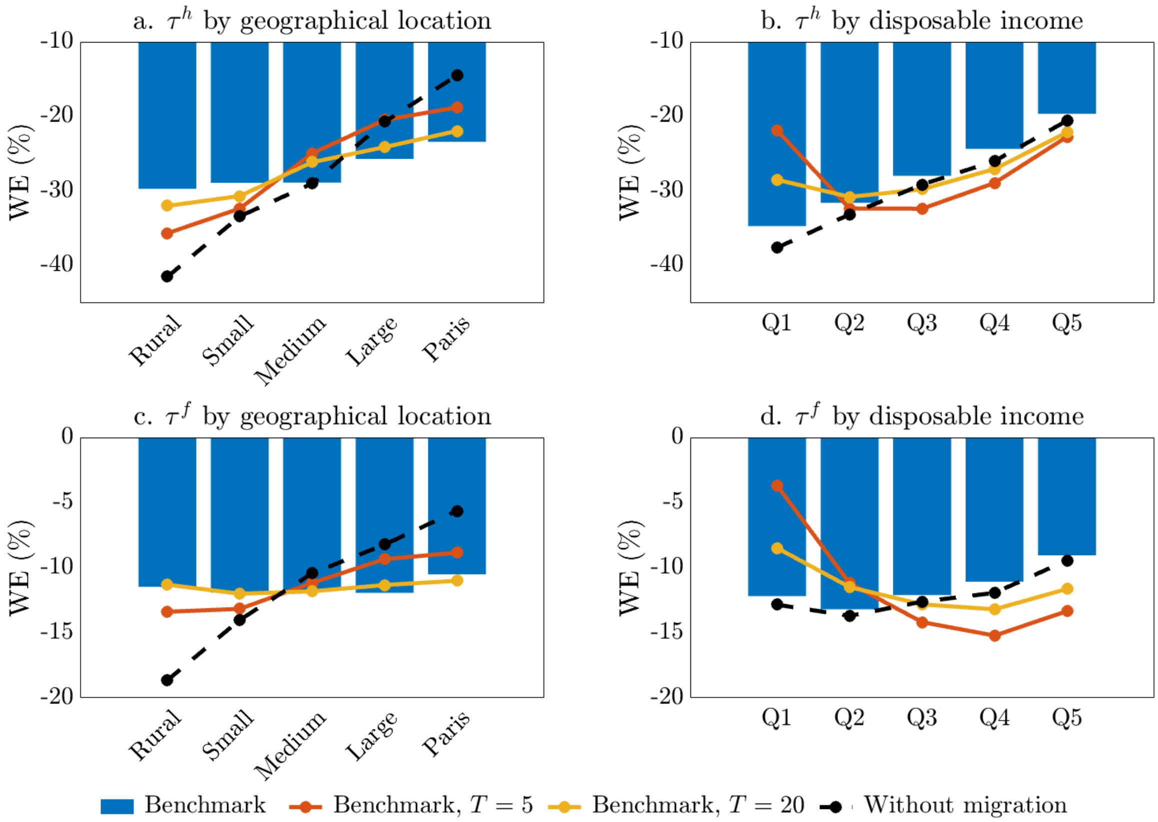
In conclusion, due to differences in households' energy consumption baskets for τ^h and firms' fossil fuel intensity for τ^f, both carbon taxes disproportionately impact rural areas and lower-income households. Migration and housing price adjustments partially mitigate the welfare costs along the geographic 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 κ, 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.

Counterfactual without migration. In Figure 7, we conduct the same experiments as above 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 of -42% for τ^h and -19% for τ^f, compared to -30% and -12% 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 prices up, and real wages down. Therefore, welfare costs in Paris are significantly higher with migration than without.

Figure 7: Welfare effect with and without migration, and at different horizons



These results highlight the critical role of migration in shaping the distributive effects of carbon taxes. In Figure 15 in Appendix, we depict the changes in population between steady states across income and geographic dimensions. For τ^h, significant composition effects occur within each region. Poor households move away from rural areas and small cities, leading to lower housing prices that attract wealthier households. The opposite trend is observed in large cities: in the new steady state, total income rises by 2.4% in rural areas and 1.1% in small cities but decreases by 3% in large cities.

The composition effect is reversed for τ^f. As wages decline in small cities, high-productivity workers migrate from small to large cities. This leads to a decrease in housing prices in small cities, which attracts poorer households. In the new steady state, average total income has decreased by 5.5% and 2.8% in rural areas and small cities, respectively, compared to the initial steady state, while it has increased by 1.6% and 4.2% in medium and large cities.

Short-run and long-run welfare effects. Migration influences the distributive effects of carbon taxes along the geographic dimension, but migration requires time, as households must accumulate savings to pay migration costs or wait for a positive productivity shock. Consequently, the welfare effects may differ between the short run and the long run. To quantify this phenomenon, we truncate the infinite discounted sum of expected utility to a finite period and compute the welfare effect for this finite horizon. Formally, for any 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 scale the "horizon-h wealth equivalent" to have the same mean as the "infinite-horizon WE," since the welfare cost increases with time. This metric answers the question: "As a percentage of my income, how much money would I need to compensate for the costs of the first h periods of the transition?".

The red and yellow lines in Figure 7 represent the WE for $T = 5$ and $T = 20$, while the blue bars correspond to $T = \infty$. As shown, the distributive effects differ significantly between the short run and the long run. For $T = 5$, the short-run welfare costs are much 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. As the population recomposition within regions described above has not yet occurred, the cost of τ^h and τ^f are concentrated in the middle of the income distribution, as illustrated by the horizon-5 decomposition in Figure 14 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.

In conclusion, we have shown that **the cost of the carbon transition for households 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% 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:[16]

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

where T is the transfer, y_i the total household's income, CTR the carbon tax revenue, and μ the scaling parameter.[17]

In the "**Benchmark *G***" scenario, the carbon tax revenue is used to increase public spending G, with transfers set to zero. In the "**Uniform**" scenario, all households receive the same transfer. In the "**Income**" scenario, we find the optimal value[18] 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 × Geography**" scenario, we optimize over five different x_k, allowing the government to apply region-specific progressivity levels.

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 for average welfare, or using Negishi weights, or with alternative rebate formulas.

[16] 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.

[17] 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: $\mu = 1/\int_i y_i^{-x_k}$.

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

Table 2: Median welfare 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	3.03	0.91	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: Welfare is computed as wealth equivalent (in % of households expenditures) over the transition.

While a uniform transfer increases median welfare by 7.3%, an optimal progressive transfer targeting low-income households yields a 29% higher welfare gain (9.4%), at the expense of high-income groups. However, as illustrated in Figure 8 below and in Table 14 in the Appendix, the "**Income**" scenario also generates welfare losses for 24.2% of households, primarily in rural areas and small cities. These are high-income households who do not receive the progressive transfer but bear the tax burden.

Therefore, we introduce our "**Income × Geography**" scenario, which allows for different income progressivity across regions. This rule increases median welfare for all groups along both the income and geography dimensions and reduces the share of losers by 10% compared to the income-only scenario. Thus, **incorporating geography into redistribution policies improves median welfare by 7.4%** (and average welfare by 7.6%) relative to the optimal transfer based solely on income.

Figure 8: Histogram of welfare gains

As shown in Figure 16 in the Appendix, our distributive results are partially driven by 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 housing prices. This reallocation generates significant migration costs during the transition, reducing overall welfare. In contrast, this effect is mitigated in the "**Income × Geography**" scenario: since transfers are less progressive in rural and small areas and more progressive in medium and large cities, households have fewer incentives to migrate, thereby lowering welfare costs.

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 several administrative datasets, household-level surveys and matched employer-employee records from France, we document that rural households consume 2.7 times more fossil fuels than urban households and are employed in firms that emit 3 times more. These patterns are consistent across other countries. We incorporate these findings into a spatial-heterogeneous agent model, featuring idiosyncratic income risks, endogenous consumption, savings, and migration choices, as well as segmented housing and labor markets, and local energy expenditure shares for both households and firms. Our approach bridges a gap in the literature by integrating spatial models, which emphasize migration, with 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, even after accounting for transitional dynamics and migration. Ignoring spatial heterogeneity in income-based transfer policies reduces overall welfare by 7%, a result that holds across different welfare criteria and recycling 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. Additionally, our findings indicate that different forms of carbon taxation generate distinct migration responses, highlighting the need for further empirical research. Finally, incorporating both inequality and migration dynamics into macroeconomic models may be essential for designing an optimal fiscal-monetary policy mix during the energy transition.

References

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).

Allen, Treb and Arkolakis, Costas (2014). "Trade and the Topography of the Spatial Economy". In: *The Quarterly Journal of Economics* 129.3, pp. 1085–1140 (cit. on p. 5).

Auclert, Adrien et al. (2021). "Using the sequence-space Jacobian to solve and estimate heterogeneous-agent models". In: *Econometrica* 89.5, pp. 2375–2408 (cit. on p. 45).

Auray, Stéphane et al. (2022). "Markups, Taxes, and Rising Inequality". In: *CREST Working Paper* (cit. on pp. 21, 46).

Bach, Laurent et al. (2024). "Les émissions de CO2 de l'industrie française et le ciblage carbone des politiques publiques". In: *IPP Working Paper* 102 (cit. on pp. 38, 39).

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 p. 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. 21).

Bilal, Adrien and Rossi-Hansberg, Esteban (2021). "Location as an Asset". In: *Econometrica* 89.5, pp. 2459–2495 (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. 49).

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. 15, 48).

Cette, Gilbert, Koehl, Lorraine and Philippon, Thomas (2019). "Labor Shares in Some Advanced Economies". In: *Working Paper # 727, Banque de France* (cit. on pp. 21, 46).

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, 14, 18, 46, 48).

Couture, Victor et al. (2024). "Income growth and the distributional effects of urban spatial sorting". In: *Review of Economic Studies* 91.2, pp. 858–898 (cit. on pp. 5, 44).

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).

Davis, Donald R and Dingel, Jonathan I (2019). "A spatial knowledge economy". In: *American Economic Review* 109.1, pp. 153–170 (cit. on p. 5).

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 et al. (2019). "State taxes and spatial misallocation". In: *Review of Economic Studies* 86.1, pp. 333–376 (cit. on p. 5).

Ferriere, Axelle et al. (2023). "On the Optimal Design of Transfers and Income Tax Progressivity". In: *Journal of Political Economy Macroeconomics* 1, pp. 276–333 (cit. on pp. 13, 21, 44, 46, 56).

Franklin, Simon et al. (2024). "Urban public works in spatial equilibrium: Experimental evidence from Ethiopia". In: *American Economic Review* 114.5, pp. 1382–1414 (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. 21, 46).

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, 19).

Golosov, Mikhail et al. (2014). "Optimal Taxes on Fossil Fuel in General Equilibrium". In: *Econometrica* 82.1, pp. 41–88 (cit. on p. 48).

Goulder, Lawrence H. et al. (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).

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. 15, 19, 47, 48).

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).

Hurst, Erik et al. (2016). "Regional redistribution through the US mortgage market". In: *American Economic Review* 106.10, pp. 2982–3028 (cit. on p. 5).

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 pp. 21, 46).

Kleinman, Benny, Liu, Ernest and Redding, Stephen J (2023). "Dynamic Spatial General Equilibrium". In: *Econometrica* 91.2, pp. 385–424 (cit. on pp. 5, 44).

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. 15).

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. 21).

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. 19, 21).

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).

Redding, Stephen J and Rossi-Hansberg, Esteban (2017). "Quantitative spatial economics". In: *Annual Review of Economics* 9, pp. 21–58 (cit. on p. 5).

Tauchen, George (1986). "Finite state markov-chain approximations to univariate and vector autoregressions". In: *Economics letters* 20.2, pp. 177–181 (cit. on p. 43).

Appendix

Table of contents

A Descriptive Evidence

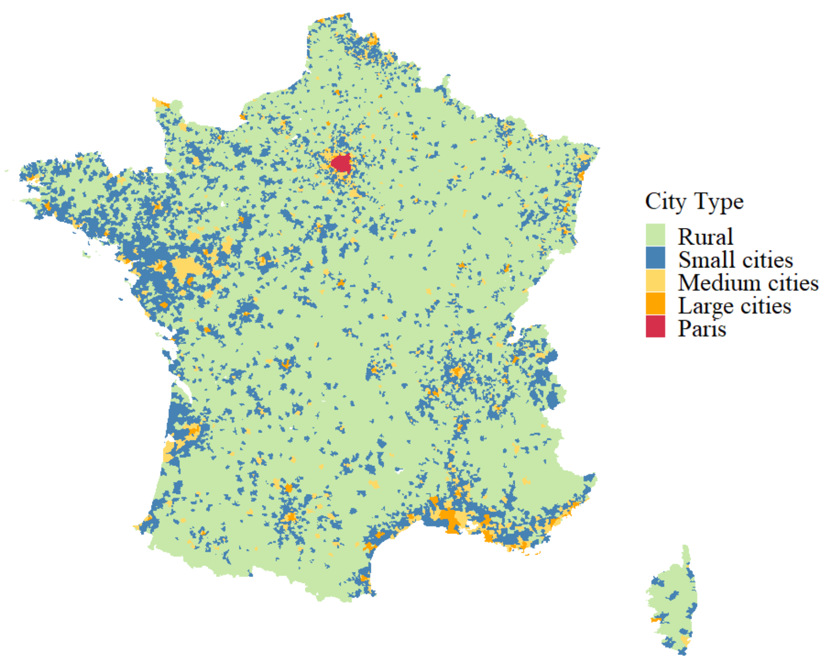
A.1 City types

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 (DADS and household-level fiscal data). Figure 9 provides a map of France illustrating these categories, using 2024 Insee geographical code.

Figure 9: 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 the size of living spaces in squared meters) 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

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

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

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

Table 4: Descriptive statistics: age groups, 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.

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 estimate 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 code (34,987 areas) and present the spatial distribution in Figure 3.

Households and size of living spaces: We use the Fideli 2017 database to assess the size of living spaces depending on income and spatial characteristics. Fideli or *Fichier Démographique d'Origine Fiscale sur les Logements et les Individus* is a structured administrative data that relates tax administration records on housing property and declared earnings through fiscal identifiers for households and dwellings. The dataset provides demographic details, household structures, income levels, social benefits received, and contextual geographic information, covering both mainland France and all overseas departments.

Table 5: Households' size of living space, in m^2

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

Sources: Fideli 2017: over 26 millions observations.

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 aggregate 3 different datasets in order to cover all emissions in France. First, we take Bach et al. (2024). They compute emission intensity, in kgCO_2eq per euro of value added, for all manufacturing subsectors (NAF code 05 to 33) in France. Second, for the 'Waste' subsector (NAF code 36-9), we use data from the CITEPA that gives total emissions of the sector in tCO_2eq. Third, for the remaining subsectors that are part of 'Agriculture', 'Other industrial activities', 'Energy', 'Transports' and 'Services', we use total emissions computed by government officials in national accounts and in the 2025 Budget Bill[19]. We report part of the data in Table 6. Finally, we build a tCO_2eq/Worker metric using annual

[19]Since 2020, the French Government publishes a green budget report, listing all expenditure having a favourable or unfavourable impact on the environment. Within this report, they also estimate total emissions per economic sectors. We focus on the year 2025 because earlier estimates excluded non-energy emissions.

value added and employment levels from 2022 Insee National Accounts. We find very heterogeneous results across sectors. 'Coke Production & Refining' and 'Metallurgy' are the most intensive in emissions with $1,422$ and 872 tCO_2eq annual emissions per worker. In the services sector, firms emit on average 1.8 tCO_2eq per worker each year.

Table 6: Emission intensity per sectors, Bach et al. (2024), CITEPA, national accounts

	NAF Code	**Emissions**^{A}	**VA**^{B}	**Employment**^{C}	**C02/Worker**^{D}
Agriculture*	01-3	1.7	46.8	314.2	250.6
Other Extractive Industries	05-9	0.7	1.7	14.3	88.9
Food Industries	10	0.4	37.3	644.6	23.8
Beverage Manufacturing	11	0.1	6.1	34.1	10.7
Textile Manufacturing	13	0.2	1.9	40.8	9.3
Clothing Industry	14	0.1	1.6	46.1	1.7
Leather & Footwear Industry	15	0.0	2.9	31.5	1.6
Woodworking & Basketry Manuf.	16	0.2	5.3	62.9	16.5
Paper & Paperboard Industry	17	0.8	5.8	58.0	75.6
Printing, Repro. of Recorded Media	18	0.1	2.8	52.8	5.8
Coke Production & Refining	19	1.9	4.9	6.4	1421.9
Chemical Industry	20	1.3	19.6	124.6	196.6
Pharmaceutical Industry	21	0.0	13.4	47.9	12.0
Rubber & Plastic Product Manuf.	22	0.1	18.4	121.5	16.8
Non-metallic Min. Product Manuf.	23	2.2	9.0	99.1	199.2
Metallurgy	24	5.2	10.4	62.4	872.1
Metal Product & Machinery	25	0.1	22.3	287.9	8.0
Computers, Electronics & Optical	26	0.0	11.5	87.0	3.4
Electrical Equipment Manuf.	27	0.1	7.3	85.7	8.7
Machinery & Equipment Manuf.	28	0.1	13.4	147.3	4.7
Automobile Industry	29	0.1	14.0	105.2	8.0
Other Transport Equipment Manuf.	30	0.0	18.7	103.2	4.7
Furniture Manuf.	31	0.1	2.3	44.4	3.1
Other Manufacturing Industries	32	0.1	5.8	85.5	3.5
Repair & Installation of Machinery	33	0.0	27.9	372.0	1.9
Energy	35	2.6	29.6	411.2	189.6
Waste	36-9	0.9	15.3	153.3	94.0
Other industrial activities*	12, 41-43	0.2	131.5	1604.2.1	17.6
Transport*	49-53	0.3	128.6	1451.0	30.3
Services*	–	0.0	1765.8	22102.2	1.8

Notes. For sectors with an *, we use sub-sectoral emission intensity from national accounts. We only report the sectoral-level value here. A: emissions in kgCOeq/€ of VA, 2022. B: Value Added 2022, €Bn. C: Employment, thousands. D: CO_2eq per worker, tCOeq/worker.

Administrative data on workers. ***Déclaration Annuelle de Données So-***

***ciales* (DADS)**. The DADS 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 DADS dataset covers all non-agricultural employees, including those in public companies, local governments, and public hospitals. It also includes data on unemployed individuals receiving benefits.

Merging DADS micro data and sectoral emissions. From the DADS 2021, we assign to each worker i the average emission intensity from its firm f. The emission intensity of firm f is computed using sub-sectoral level emission intensity from Table 6 and firm's share in total employment. In each group (city or quintile), we then compute the average emission intensity 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 emission-intensive sectors as those whose share in total emissions is above their share in total value added, *i.e.* all industrial sectors, 'Agriculture', 'Energy' and 'Transport' sectors. We additionally report the share of workers in those sectors in Table 7.

Table 7: Share of workers (%) in each sectors, by geography and income quintile

Sector	**NAF Code**	**Rural**	**Small**	**Medium**	**Large**	**Paris**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Agriculture	01-3	3.1	1.6	0.9	0.6	0.1	2.6	1.8	1.3	0.8	0.4
Industry	–	21.2	17.9	14.4	11.1	8.7	8.0	10.9	17.0	21.3	20.6
Coke and Refining	19	0.03	0.03	0.03	0.02	0.01	0.00	0.00	0.01	0.01	0.12
Chemical Industry	20	0.61	0.55	0.47	0.30	0.40	0.12	0.17	0.30	0.55	1.28
Non-metallic Manuf.	23	0.60	0.40	0.25	0.13	0.08	0.09	0.15	0.37	0.50	0.52
Metallurgy	24	0.42	0.32	0.24	0.13	0.02	0.04	0.09	0.22	0.43	0.49
Energy	35	0.8	0.5	0.5	0.5	0.6	0.1	0.1	0.1	0.6	1.8
Transport	49-53	5.2	5.0	5.0	4.1	4.4	2.7	3.5	5.7	7.4	4.7
Services	–	69.7	75.1	79.3	83.8	86.3	86.5	83.6	75.8	70.0	72.5
Sum	–	100	100	100	100	100	100	100	100	100	100

Notes. We use the 2021 cross-section of the DADS. We remove negative income values and we merge individuals present more than once in the dataset, ending up with 3,528,153 observations.

Spatial distribution of sectoral emissions. Using the DADS 2021 dataset, 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 3,295,317 worker-level observations, which are aggregated into 34,607 geographical units.

A.4 Regression

OLS Regression. 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 8 below. We use the regression coefficients to build average energy consumption shares in Figure 1 and average emissions per worker in Figure 2.

Table 8: Regressions

	y_i: consumption share BdF 2017			y_i: emissions per worker DADS 2021
	(1) Energy share	(2) Fossil fuel share	(3) Electricity share	(4)
Intercept	12.00***	6.77***	5.23***	20.31***
	(0.32)	(0.29)	(0.16)	(0.10)
Q2	−0.72***	0.15	−0.88***	−0.99***
	(0.20)	(0.18)	(0.10)	(0.10)
Q3	−1.05***	0.21	−1.27***	0.79***
	(0.20)	(0.18)	(0.10)	(0.10)
Q4	−1.65***	−0.04	−1.61***	4.45***
	(0.20)	(0.18)	(0.10)	(0.10)
Q5	−2.28***	−0.51**	−1.77***	8.98***
	(0.20)	(0.18)	(0.10)	(0.10)
Small	−1.89***	−1.79***	−0.10	−6.59***
	(0.22)	(0.20)	(0.11)	(0.09)
Medium	−2.50***	−2.01***	−0.49***	−9.12***
	(0.22)	(0.20)	(0.11)	(0.10)
Large	−4.97***	−3.68***	−1.28***	−13.2***
	(0.17)	(0.15)	(0.08)	(0.11)
Paris	−7.11***	−5.54***	−1.56***	−15.8***
	(0.21)	(0.19)	(0.11)	(0.10)
Age	0.06***	0.03***	0.02***	–
Household size	−0.11*	0.16***	−0.27***	–
Observations	16,739	16,739	16,739	3,528,153

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 both datasets, we only keep observations with strictly positive income: disposable income in BdF 2017, wage in DADS 2021. *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

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 et al. (2023) 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 – see Ferriere et al. (2023), Couture et al. (2024) or Kleinman, Liu and Redding (2023). 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 prices $\{p_1^H, p_2^H, p_3^H, p_4^H, p_5^H\}$ (segmented housing markets), local outputs $\{Y_1, Y_2, Y_3, Y_4, Y_5\}$ (segmented labor markets), 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 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 9: 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 et al. (2023)
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 10: 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 11, we use the *Revenus et patrimoine des ménages, Édition 2021*, that we reproduce below:

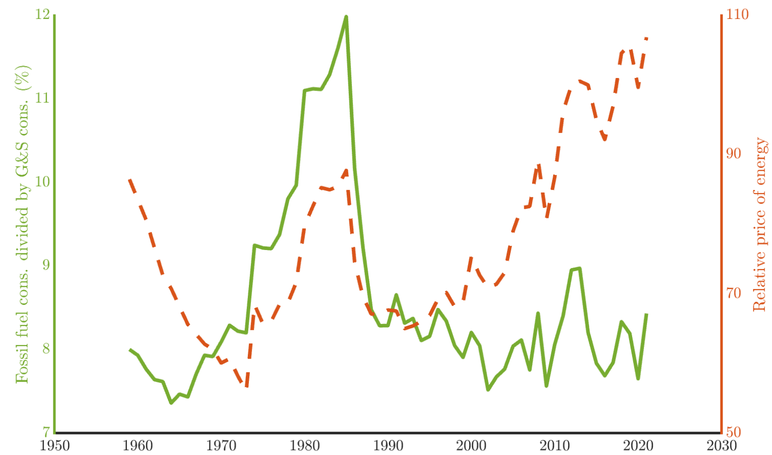
Table 11: Revenues and taxes by income decile (thousand euros)

	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 10, we use French longitudinal aggregate data taken from Insee 2022 national accounts, and show that 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, as explained in Hassler, Krusell and Olovsson (2021).

Figure 10: 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:

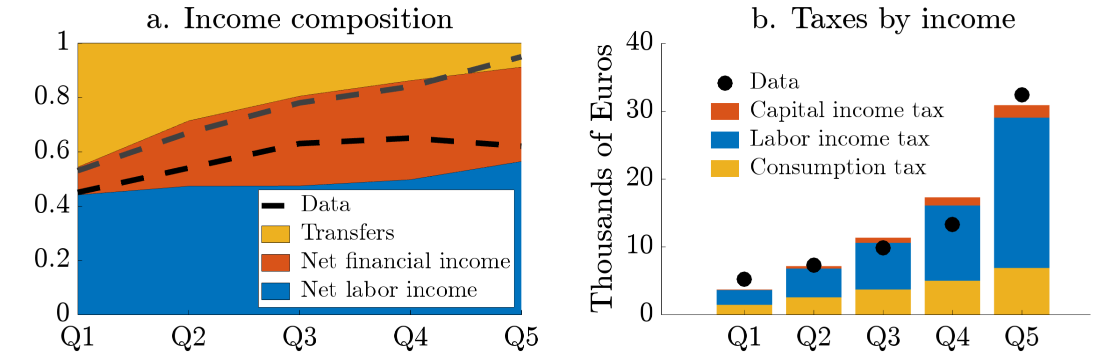
$$\Delta \ln(e^h_t) - \Delta \ln(c_t) = -\sigma \Delta \ln(p^h_t) + \epsilon_t$$

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 11, we show the income composition across income quintile, and total taxes paid by households.

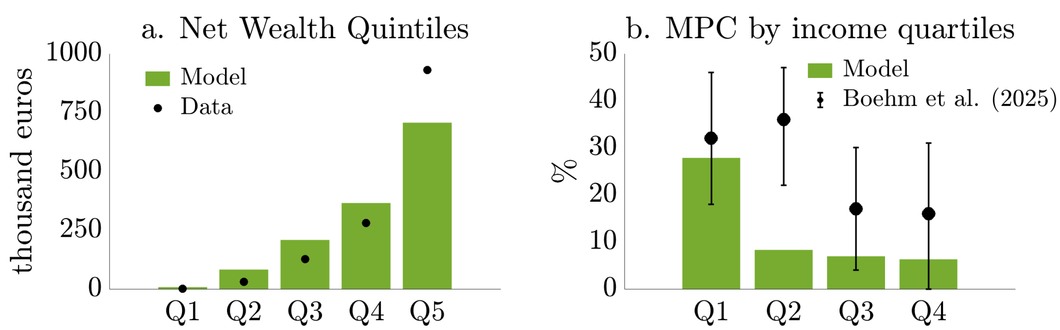
Figure 11: Income composition and taxes by income quintile



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 12: 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 13, 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 prices (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 13: Decomposition of the welfare effect

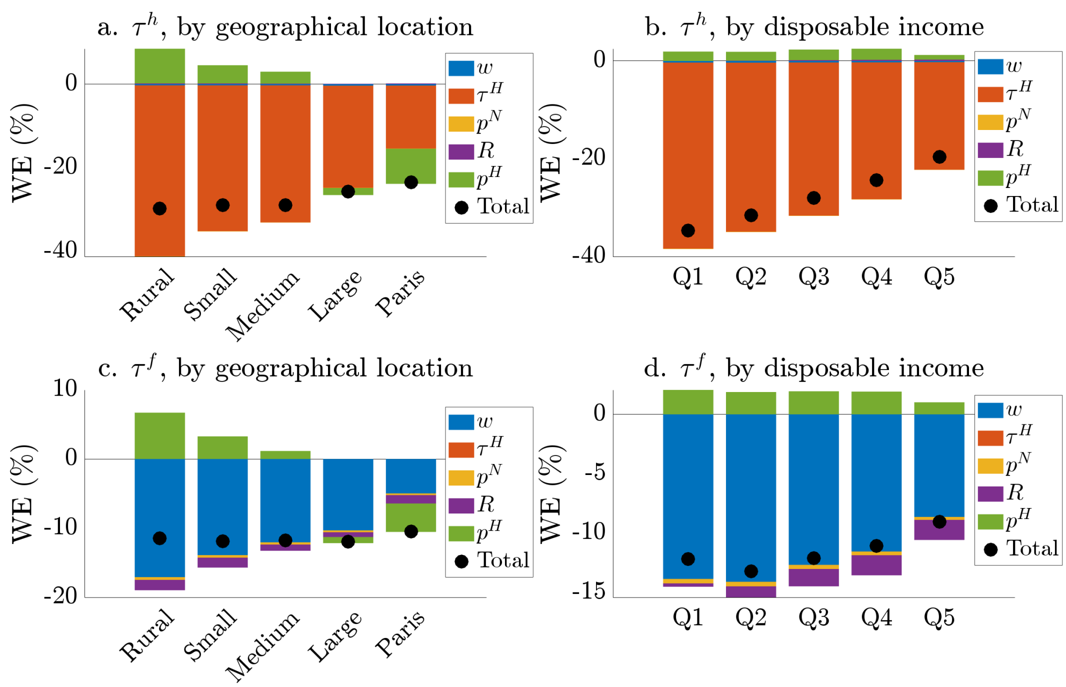


Figure 14 is the same decomposition, but considering only the welfare changes during the first 5 periods of the transition.

Figure 14: Decomposition of the welfare effect at horizon $t = 5$

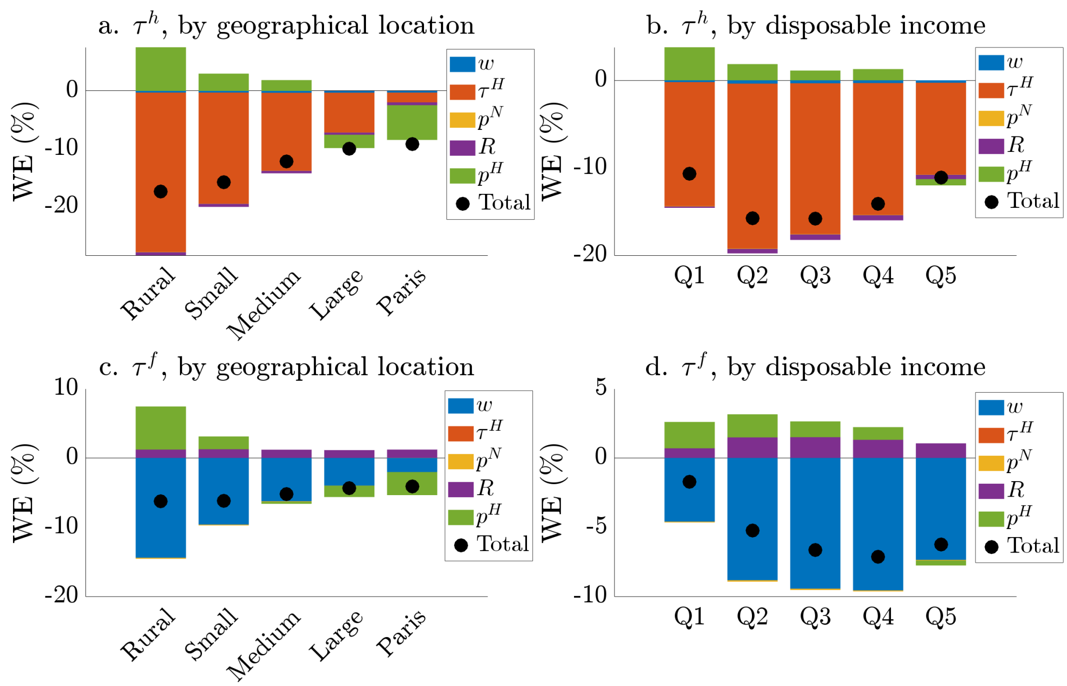
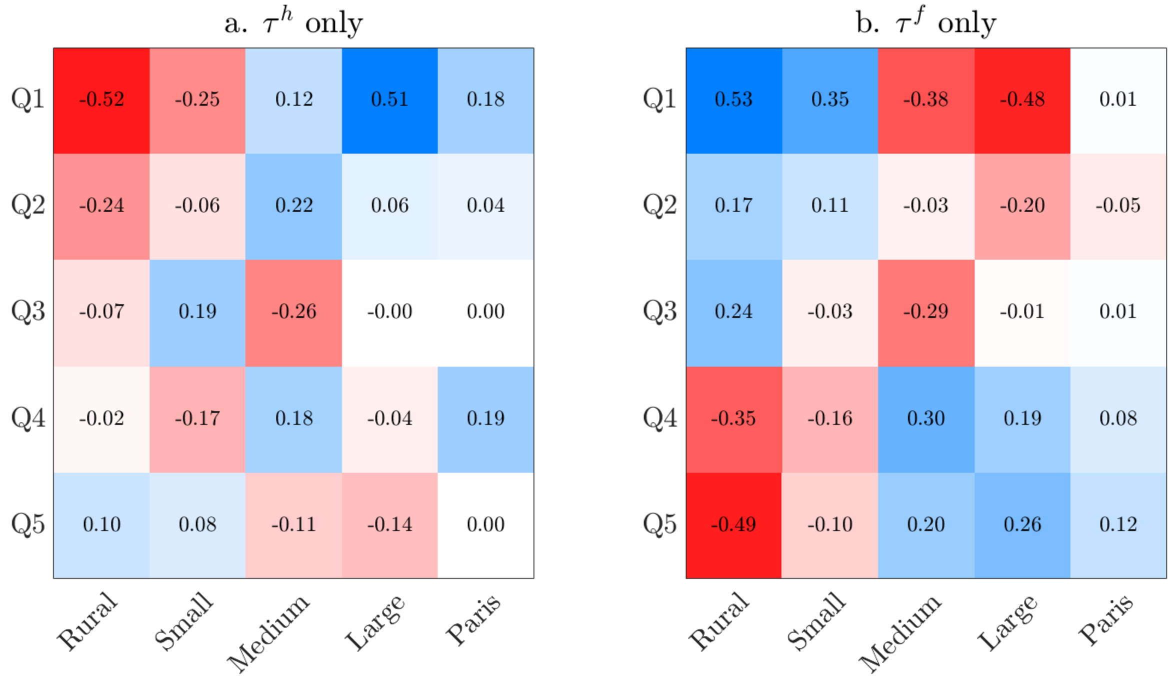


Figure 15 shows, for each Region × Income quintile, the change in population between the two steady states. The sum of each line is equal to 0, as the share of households in each disposable income quintile is always 20%; the sum of each column can be different from 0, as households migrate between regions.

Figure 15: 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, the share of households in rural areas that are in the 1st quintile decreases by 0.52% 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 price.

E Additional results – Section 5

E.1 τ^h vs τ^f

In Table 12, we show the optimal values of τ^h and τ^f required to reduce emissions by 10%. In the benchmark complete model, 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 12: Optimal taxes to reduce emission 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 13 below is the average welfare, computed as the average wealth equivalent (in % of households expenditures) over the transition.

Table 13: Average welfare 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: Welfare is computed as wealth equivalent (in % of households expenditures) over the transition.

In Table 14, 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 14: 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 16, 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 less migrations, as rich households in rural areas receive a transfer and therefore are not forced to migrate.

Figure 16: Migration dynamics

Notes: 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 in rural areas that are in the 1st quintile increases by 0.09% 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 15, 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 15:

Table 15: Average welfare 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: Welfare is computed as wealth equivalent (in % of households expenditures) over the transition.

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 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 17 compares our optimal inverse-rule formula with the transfer rule 7. The rule 17 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 16. With this transfer rule, we again find that allowing for spatial specific progressivity parameters ξ_k[20] enhances aggregate welfare by +8.3%.

[20]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 17: Inverse formula vs. formula 7

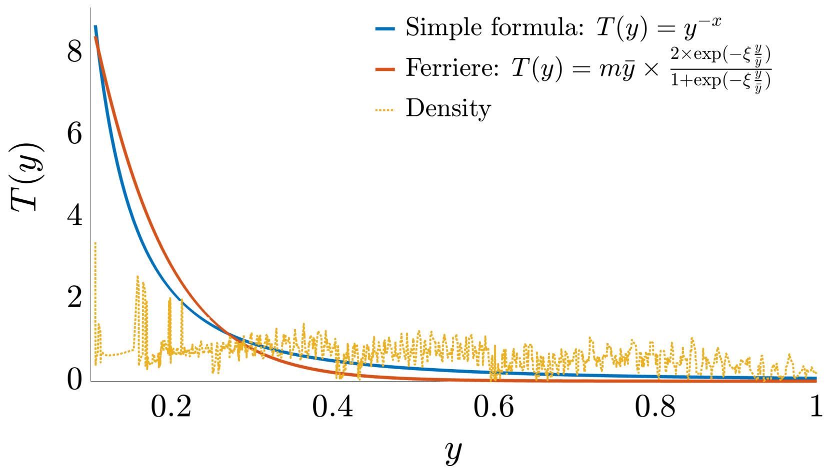


Table 16: Average welfare by location and income, alternative transfer rule

	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: Welfare is computed as wealth equivalent (in % of households expenditures) over the transition.

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 17, 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 17: Average welfare 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: Welfare is computed as wealth equivalent (in % of households expenditures) over the transition. 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 18 shows the median welfare, computed as wealth equivalent, between our benchmark model (general equilibrium) and this partial simulation.

Table 18: Median welfare 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: Welfare is computed as wealth equivalent, in % of households expenditures. 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, housing prices, 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 19. These adjustments do not alter our overall quantitative findings.

Table 19: Average welfare 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: Welfare is computed as wealth equivalent, in % of households expenditures. Last column: inequality ratio, defined as the percentage change between the first and the fifth column.