

# Geography versus Income: The Heterogeneous Effects of Carbon Taxation

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## Geography versus Income: The Heterogeneous Effects of Carbon Taxation\*

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## **Géographie ou Revenus : les effets distributifs de la taxation carbone**

Les effets distributifs de la taxation carbone sont cruciaux pour son acceptabilité politique et dépendent à la fois des inégalités de revenus et de facteurs géographiques. En utilisant des données d'enquêtes et administratives françaises, nous montrons que les ménages ruraux consacrent une part de leur consommation 2,8 fois plus élevée aux combustibles fossiles que les ménages urbains, et travaillent dans des entreprises qui émettent 2,7 fois plus de gaz à effet de serre. Nous intégrons ces éléments dans un modèle spatial à agents hétérogènes avec choix endogènes de migration et d'accumulation de richesse. Après une augmentation des taxes carbone, nous estimons que les ménages ruraux subissent des pertes de bien-être 20 % plus élevées que les ménages urbains. Ces pertes sont amplifiées à court terme par une baisse des salaires, mais partiellement compensées à long terme par la migration et la baisse des prix de l'immobilier. Par rapport à des transferts uniformes, cibler à la fois le revenu et la localisation géographique augmente les gains de bien-être médians d'un tiers de plus que ceux obtenus par le seul ciblage du revenu. Nous concluons que les mécanismes de taxation du carbone doivent tenir compte des disparités spatiales afin d'améliorer leur acceptabilité politique.

**Mots-clés :** Taxe carbone, énergie, politique fiscale, inégalités, géographie, dynamiques spatiales, migration

Codes JEL : C61, E62, H23, Q43, Q58, R13

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## **Geography versus Income: The Heterogeneous Effects of Carbon Taxation**

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 have a fossil fuel consumption share 2.8 times higher than that of urban households and are employed in firms that emit 2.7 times more greenhouse gases. We incorporate these insights into a spatial heterogeneous agent model with endogenous migration and wealth accumulation, linking spatial and macroeconomic approaches. After an increase in carbon taxes, we quantify that rural households face 20% higher welfare losses than urban households. These losses are amplified in the short run by wage declines, but partially offset in the long run by migration and lower rents. Compared to uniform transfers, jointly targeting income and geographic location increases median welfare gains by one third more than those achieved by income targeting alone. We conclude that carbon policies should account for spatial differences to improve political feasibility.

**Keywords:** Carbon tax, energy, fiscal policy, inequalities, geography, spatial dynamics, migration.

**JEL Code :** C61, E62, H23, Q43, Q58, R13

# 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 the existing literature has predominantly focused on the “rich versus poor” dimension of the energy transition burden, less attention has been given to the geographical heterogeneity in energy consumption patterns. This paper addresses this gap by providing detailed empirical evidence on regional disparities and integrating these patterns into a rich quantitative model.

In the first part of the paper, we systematically document the distribution of direct emissions across both households and firms, using several datasets covering the French economy. We 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 sector-level greenhouse gases emissions. In both cases, we describe how direct emissions are distributed across income levels and city sizes.

In the second part of the paper, we integrate these emission patterns into a new spatial heterogeneous-agent model that captures heterogeneity in both income and geography. 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. Households endogenously choose whether to migrate in response to 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. Under a welfare-maximizing planner with an emissions constraint, we evaluate a range of revenue-recycling scenarios, from increased public spending to targeted transfers based on location and income. Our paper yield 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 spend 2.8 times more fossil fuels, as a share of consumption, 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. Matching employer-employee records with sectoral-level emissions data, we find that rural workers are twice as likely as their urban counterparts to be employed in emissions-intensive sectors, such as agriculture and manufacturing. By attributing firm-level greenhouse gases emissions to employees based on firm size and sectoral emission intensity, we find that rural households are employed in firms emitting 2.7 times more GHGs than those located in the Parisian agglomeration. 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, we target a 10% reduction in emissions and use the additional fiscal revenues to increase public spending that does not enter utility. We find that median welfare losses in rural areas are 20% higher than those in the Parisian agglomeration ( $-1.1\%$  vs.  $-0.9\%$  measured as a welfare-equivalent reduction in wealth at each period, expressed as a share of initial income). 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 fossil fuels are necessities, disproportionately burdening low-income households. The firm tax is less regressive, as it primarily reduces wages – adversely affecting middle-income households – and lowers interest rates, which harms 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 rents. 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 median welfare by 0.04 point, and mean welfare by 0.13 point**. Our optimal transfer recycling policy – targeting both income and location – outperforms income-only targeting by 0.04 point and uniform transfers by 0.17 point. Relative to uniform transfers, jointly targeting income and geographic location increases median welfare gains by one third more than income targeting alone. 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 gen-

eral equilibrium distributive effects of carbon taxation by jointly examining its impact on both households and firms, incorporating both income and spatial heterogeneity. This framework bridges two key strands of the literature: the distributive effects of carbon taxation, and the modeling of income and geographical heterogeneity among households.

The literature on the *distributive effects of carbon taxation* examines the heterogeneous fiscal incidence of carbon taxes across households, using micro-simulation, Computable General Equilibrium (CGE), or heterogeneous-agent general equilibrium models. The general approach is to link the household 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 fossil fuels for housing and transportation) and the indirect effect (firms use energy as an input, which affects the prices of other inputs, such as capital and labor, thus influencing income distribution). Based on micro-simulations, [Cronin, Fullerton and Sexton \(2019\)](#) for the U.S. and [Douenne \(2020\)](#) in the French context conclude that carbon taxes are regressive, with most of the heterogeneity occurring within income quantiles. We confirm that carbon taxes are regressive and explicitly model this *within-quantile* heterogeneity by introducing geographical differences, which are a key determinant of tax burden disparities across households. Within the CGE literature, [Rausch, Metcalf and Reilly \(2011\)](#) and [Goulder et al. \(2019\)](#) conclude that the progressivity of *source-side* effects (related to changes in relative factor prices) offsets the regressive *use-side* effects (related to the composition of total expenditures). Compared to these studies, we endogenize income and wealth distributions by incorporating idiosyncratic income risk, and 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 use the revenue to reduce distortive 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 area. 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 rents, 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 household and firm carbon 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 rebate policies. Finally, Section 6 concludes.



# 1 Descriptive Evidence

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

## 1.1 Households' direct emissions

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

*Data.* We use French microdata from the 2017 *Budget de Famille* (BdF) Insee survey, covering over 16,000 households. From this consumer expenditure survey, we construct household-level fossil fuel expenditures by adding up fuels for heating and those used in vehicles. Fossil-fuel consumption from transportation and heating make up for more than 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.<sup>1</sup> Throughout the paper, we classify locations into five city types: Rural, Small cities, Medium cities and Large cities based on population size, and the Parisian agglomeration.<sup>2</sup> These categories represent 23.5%, 26.0%, 18.5%, 13.4%, and 18.6% of the population, respectively. For a fair comparison, we also categorize households into five income groups, ranked by disposable income quintiles.

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

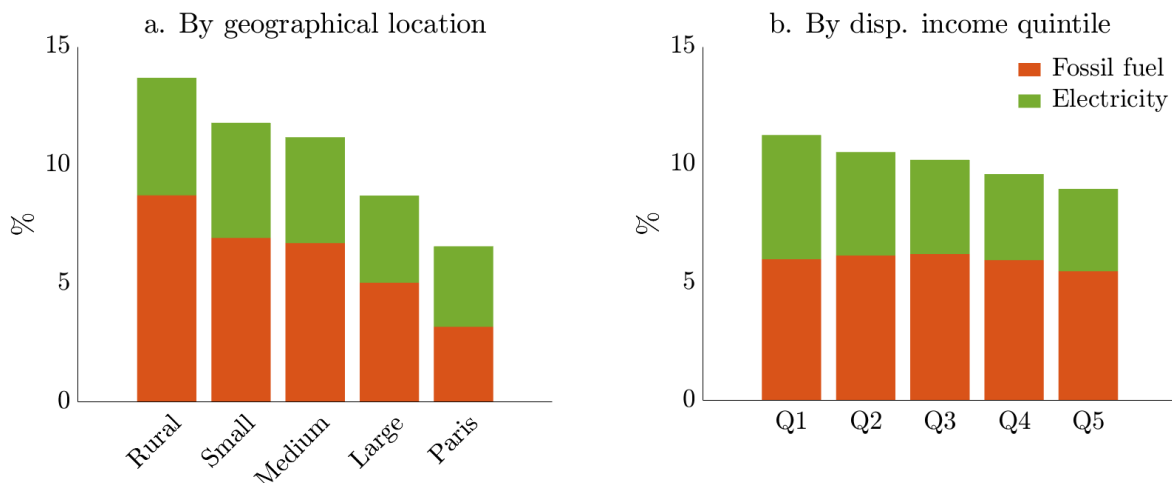
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<sup>1</sup>In the BdF survey, as in the US Consumer Expenditure Survey, it is not possible to distinguish between electricity expenditures for housing purposes and those for charging car batteries.

<sup>2</sup>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, the Parisian agglomeration or the urban unit of Paris: includes departments 75, 92, 93 and 94, as defined by Insee. In Appendix A, we provide a map of France corresponding to these categories.

type and income quintile, are shown in Figure 1. One can interpret these shares as the mean energy share in each city type (or each income quintile) if the city had the same characteristics as the whole population. While total energy is a necessary good — its share decreases from 11.3% for the first income quintile (Q1) to 8.9% for the fifth quintile (Q5) — the fossil fuel share remains flat across the income distribution, at approximately 5.9% of total expenditures. In contrast, geography strongly predicts energy consumption: rural households consume 2.1 times more energy than Parisians (13.7% versus 6.5%) and 2.8 times more fossil fuels (8.7% versus 3.1%). We then impute the fossil fuel share for all households in France using the complete set of fiscal declarations from households in 2021.<sup>3</sup> We present its spatial distribution in Figure 3, by averaging fossil fuel shares at the city code level.

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



**Note:** share of fossil fuel and electricity in total consumption expenditures, results net of controls (details in Appendix A.4). These are the mean energy share in each group (city type, income quintile) if the group had the same characteristics as the whole population. Paris: Parisian agglomeration or urban unit of Paris as defined by Insee.

**Source:** Authors' computations using Budget de Famille 2017

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 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

<sup>3</sup>See Appendix A for details.

administrative data<sup>4</sup> also reveals that rural households have nearly twice the living space of households living in the Parisian agglomeration — an average of 105.6 square meters compared to 64 square meters in the urban unit of 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 the Parisian agglomeration, compared to 4% for Q1 and 3.4% for Q5. Rural households almost universally own a car (93%) and use it for commuting (48%), whereas Parisian households rely more on public transportation and own cars less often. The number of vehicles and the necessity of commuting increase with income, resulting in relatively 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.

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<sup>4</sup>Supplementary data is available in Appendix A.

Table 1: Energy share in total consumption (%) for several countries

|                             | <b>Rural</b> | <b>Towns</b> | <b>Cities</b> | <b>Q1</b>   | <b>Q2</b>   | <b>Q3</b>   | <b>Q4</b>   | <b>Q5</b>   |
|-----------------------------|--------------|--------------|---------------|-------------|-------------|-------------|-------------|-------------|
| <b>France (sum)</b>         | <b>11.8</b>  | <b>10.3</b>  | <b>7.9</b>    | <b>10.3</b> | <b>10.0</b> | <b>10.3</b> | <b>9.8</b>  | <b>8.6</b>  |
| 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         |
| <b>Germany (sum)</b>        | <b>13.7</b>  | <b>12.6</b>  | <b>10.7</b>   | <b>11.7</b> | <b>12.3</b> | <b>12.1</b> | <b>11.9</b> | <b>11.1</b> |
| 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         |
| <b>Italy (sum)</b>          | <b>14.1</b>  | <b>12.2</b>  | <b>9.8</b>    | –           | –           | –           | –           | –           |
| electricity & gas (housing) | 6.7          | 5.8          | 5.0           | –           | –           | –           | –           | –           |
| transport costs incl. fuels | 7.4          | 6.4          | 4.8           | –           | –           | –           | –           | –           |
| <b>Netherlands (sum)</b>    | <b>10.4</b>  | <b>10.2</b>  | <b>9.1</b>    | <b>7.4</b>  | <b>8.4</b>  | <b>9.3</b>  | <b>9.6</b>  | <b>11.0</b> |
| 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         |
| <b>Spain (sum)</b>          | <b>12.6</b>  | <b>11.0</b>  | <b>8.5</b>    | <b>10.2</b> | <b>11.0</b> | <b>10.9</b> | <b>10.0</b> | <b>9.1</b>  |
| 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         |
| <b>UK (sum)</b>             | <b>14.3</b>  | <b>12.8</b>  | <b>11.2</b>   | <b>11.4</b> | <b>12.6</b> | <b>12.2</b> | <b>12.5</b> | <b>11.7</b> |
| 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         |
| <b>US (sum)</b>             | <b>8.3</b>   | <b>7.1</b>   | <b>5.7</b>    | <b>8.8</b>  | <b>8.9</b>  | <b>7.7</b>  | <b>6.9</b>  | <b>4.8</b>  |
| electricity & gas (housing) | 3.9          | 3.3          | 2.8           | 4.9         | 4.5         | 3.6         | 3.1         | 2.2         |
| fossil fuels (transport)    | 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, Eurostat 2015 HBS for the UK, 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, have higher emissions and are therefore more impacted by carbon taxes. Moreover, these sectors are unevenly distributed across regions and occupations, meaning that both income and geography play a role in determining the firms where households are employed. This, in turn, shapes the distribution of the indirect costs of carbon taxes.

*Data.* We use administrative matched employer-employee data from France known as BTS-Salariés.<sup>5</sup> The BTS dataset has two advantages. First, it is exhaustive, containing more than 60 million observations in each cross-section, providing rich demographic, geographic, and plant-level information. Second, it has a panel version that covers the entire work history of a representative set of workers ( $\sim 3$  million individuals).<sup>6</sup> 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 2022 National Accounts.<sup>7</sup> To assess workers’ exposure to a carbon tax on firms, we compute GHGs emissions per worker in each establishment of the economy. Using sectoral-level emissions and establishment’s share in sectoral labor force, we construct plant-level emissions. We then build worker-level emissions by dividing plant-level emissions by employment. We favor establishment-level estimates since biggest firms may own several establishments operating in heterogeneous sectors. As a robustness check, we do the same exercise using firm-level data in Appendix A.3 and find very similar results.

Our method has several limitations. First, it assumes homogeneous emissions intensity within each sector, which may not hold in practice due to differences in technology, scale, or production processes across firms. Second, we allocate emissions equally across all workers within a firm, implicitly assuming that all occupations contribute equally to emissions. However, some roles are likely more carbon-intensive than others (e.g., production versus administrative tasks). Incorporating more granular, firm-level or

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<sup>5</sup>BTS-Salariés: *Base Tous Salariés : fichiers Salariés..* Notice that in this dataset, we only consider employees and not independent self-employed workers. For instance in the agricultural sector, we do not cover self-employed farmers.

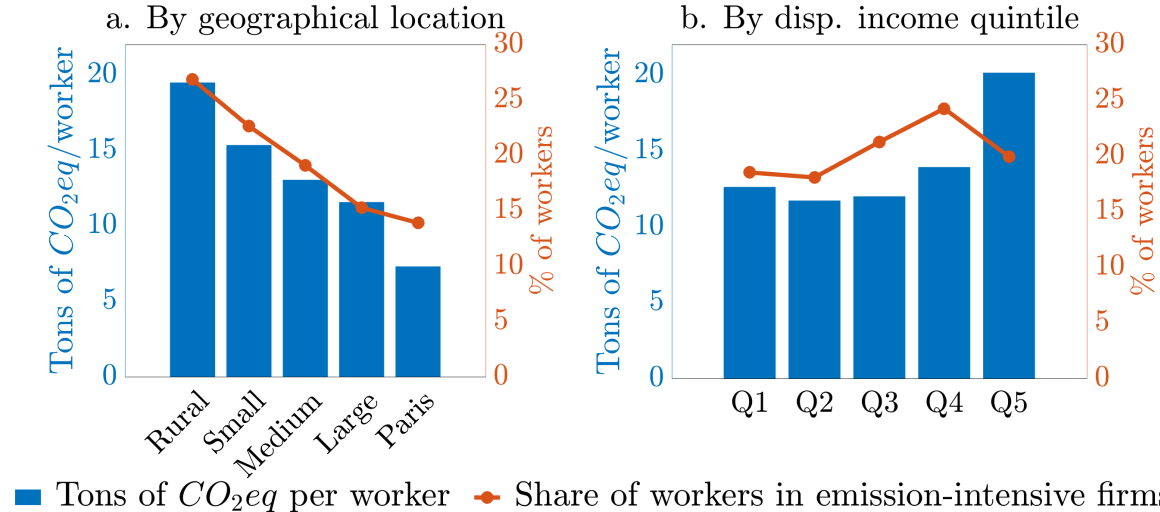
<sup>6</sup>We use the panel dimension of the dataset to analyze mobility rates across regions.

<sup>7</sup>See Appendix A.3 for details.

occupation-level data could improve the precision of our estimates and represents a promising avenue for future research. To our knowledge, such data does not currently exist in France.

*Empirical results.* We regress households’ “tons of CO<sub>2</sub>eq per worker” on city type, income quintile, as described in Appendix A.4. The predicted tons of CO<sub>2</sub> 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.<sup>8</sup> Figure 2 reveals that rural households work in firms that are 3 times more polluting than households in the Parisian agglomeration (19.5 tons of CO<sub>2</sub> per worker versus 7.3). Moreover, considering that rural areas account for 24% of the population, compared to 19% for the Parisian agglomeration, we find that firms employing rural residents account for 36% of total firms’ emissions, versus 9% for Paris. Along the income dimension, wealthier households tend to work slightly more in emissions-intensive firms. But the gradient is much less pronounced compared to the geography dimension.

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



**Note:** tons of CO<sub>2</sub>eq imputed per worker, controlling for variables detailed in Appendix A.4. It represents the average *t*CO<sub>2</sub>eq/worker in each group (city type, income quintile) if the group had otherwise the same characteristics as the whole population. Paris: Parisian agglomeration or urban unit of Paris as defined by Insee.

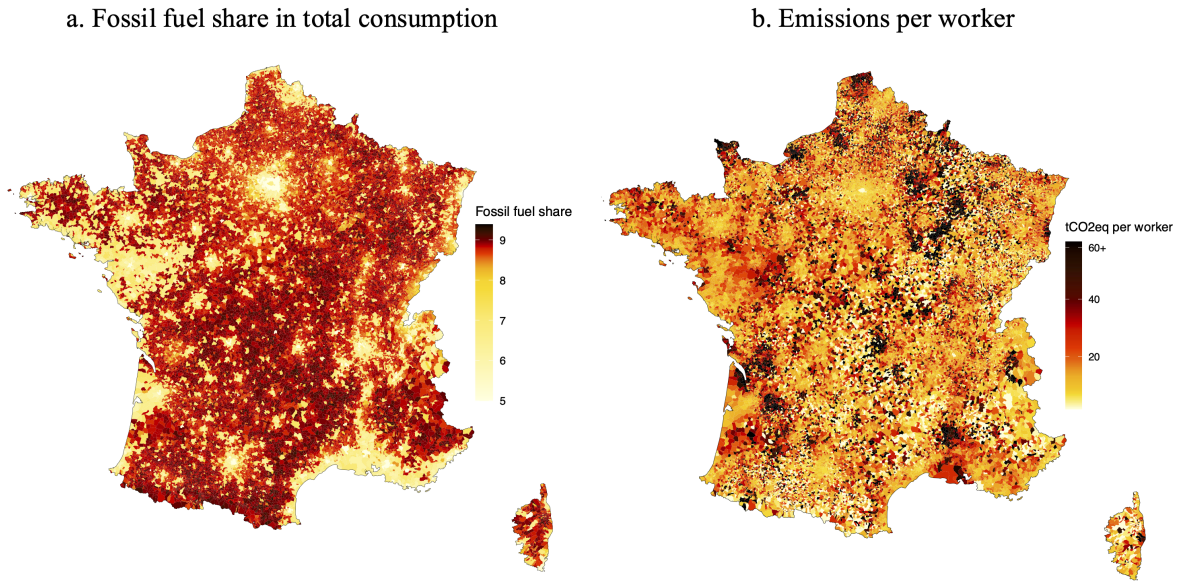
**Source:** Authors’ computations using 2022 BTS-Salariés and National Accounts

We provide a sectoral decomposition along the income and geography dimensions in Table 6 to explain these results. Workers in the two most polluting sectors, agriculture and industry, heavily concentrate in rural areas. While 3% and 14.2% of rural house-

<sup>8</sup>Emissions-intensive sectors are defined as those with emissions intensity above 5tCO<sub>2</sub> per worker.

holds are employed in these sectors, only 0.1% and 4.3% of households in the urban unit of Paris work in them. In contrast, 0.4% and 15% of high-income households (Q5) work in agriculture and industry, compared to 2.5% and 5.6% of households in the first income quintile (Q1). In Table 7, we additionally show that rural households represent 46% of all agriculture workers, 42% of mining and quarrying workers, 30% of manufacturing workers, 28% of energy workers or 22% of construction and transportation workers. Those numbers are respectively: 0.4%, 3%, 5%, 12% and 10% for Parisian households. Therefore, since both rural and wealthier households are more likely to work in emissions-intensive sectors, they may be more affected by the introduction of a carbon tax on energy consumed by firms.

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



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

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



## 2 A spatial heterogeneous-agent model

We combine heterogeneous-agent à la [Aiyagari \(1994\)](#), with idiosyncratic productivity shocks leading to income and wealth heterogeneity, to spatial models, with segmented labor and housing markets, different subsistence energy levels by living areas, and endogenous migration choice. Our productive sector is composed of a regional final good producer in each living area, which uses capital, labor, electricity and imported fossil fuel as intermediate inputs. Another national representative firm produces electricity using capital and imported fuel. Finally, the fiscal authority has a complete set of instruments: a progressive labor income tax  $\Gamma(\cdot)$ , a flat capital income tax  $\tau^k$ , a VAT tax  $\tau^{\text{VAT}}$  and carbon taxes on households  $\tau^h$  or firms  $\tau^f$ . Carbon tax revenue is used either to increase public spending or to implement targeted transfers. The algorithms used to solve the model are explained in [Appendix B](#).

### 2.1 Households

The economy is populated by an infinite amount of households indexed by  $i$  that are heterogeneous in two dimensions. The “vertical” heterogeneity is related to the idiosyncratic productivity process  $z$ , creating a distribution for wealth and income. The “horizontal” heterogeneity is related to the living area, with several household types  $k$  ranking households from “rural” to “urban”, depending on the size of the city they live in. The living area determines the minimum subsistence energy consumption level  $\bar{e}(k)$ , the energy mix parameter  $\gamma_h(k)$ , housing price  $p^H(k)$ , wage  $w(k)$ , and the mean and variance of the idiosyncratic productivity shock, so that the individual productivity is denoted  $z_i(k)$ . Households optimally choose the city type, taking into account a fixed migration cost:  $\kappa(k, k') \geq 0$ . As in [Ferriere et al. \(2023\)](#), we assume a preference shock that follows a Gumbel distribution with variance  $\varrho$ .

Households maximize intertemporal utility, choosing consumption  $c$ , housing consumption  $H$ , asset  $a'$  at the beginning of next period, energy bundle  $e^h$  (composed of electricity  $N^h$  and fossil fuel  $F^h$  with the carbon tax  $\tau^h$ ), subject to their budget constraint, their idiosyncratic productivity process and a borrowing constraint. Households supply an exogenous level of labor  $\bar{l}$ . Each household  $i$  of type  $k$  solves the following program<sup>9</sup> (omitting subscript  $i$  for clarity):

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<sup>9</sup>Denoting  $a$  the assets at the beginning of the period,  $z$  the idiosyncratic productivity, and with  $x'$  the next period variable  $x$ , the Bellman equation is defined as  $V(a, k, z) = \max_{u, a', k'} \left\{ \frac{u^{1-\theta}-1}{1-\theta} + \beta \mathbb{E}[V(a', k', z') | k, z] \right\}$ , such that Equations (1) to (5) hold.



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

subject to:

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

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

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

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

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

**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  $\sigma$ . Here,  $\Lambda_C$ ,  $\Lambda_H$  and  $\Lambda_E$  control the share of expenditures devoted to  $c$ ,  $H$  and  $e^h$ , and  $\epsilon_C$ ,  $\epsilon_H$  and  $\epsilon_E$  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  $\epsilon_h$ , 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  $\tau^{\text{VAT}}$ . Fossil fuel with relative price  $p_t^F$  is subject to an excise carbon tax  $\tau_t^h$ . On the revenue side, labor income is taxed according to a progressive tax rule  $\Gamma(\cdot)$  defined later. Capital income is subject to a flat tax at rate  $\tau^k$ . Finally, households receive lump-sum transfers from the fiscal authority, which may depend on their disposable income level or place of

residence. On the expenditure side, revenues can be used for consumption, savings, or covering migration costs.

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

Finally, **Equation 5** depicts the borrowing constraint leading to imperfect capital markets. Households cannot borrow more than  $-\underline{a}$ , so that some agents will be constrained and “hand-to-mouths”, creating households with high marginal propensity to consume at the bottom of the wealth distribution.

## 2.2 Production: goods, energy and housing

### 2.2.1 Regional Goods & Services sector

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

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

such that

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

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

$\omega_y(k)$  is region-specific, reflecting the fact that carbon-intensive industries are often located in rural areas, whereas less intensive service firms are more common in urban areas. All other parameters ( $\delta, \alpha, \sigma_y, \gamma_y, \epsilon_y$ ) are similar across regions. Since labor supply is not uniformly distributed and production function parameters differ across regions, wages  $w(k)$  are region-specific. [Hassler, Krusell and Olovsson \(2021\)](#) points toward a very low short-run substitutability between energy and other inputs once the technology factors have been chosen. Moreover, [Casey \(2024\)](#) shows that Cobb-Douglas production functions with energy inputs vastly overestimate transitional emissions adjustments. Both papers motivate our choice for a CES production function, with  $\sigma_y$  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 substitution governed by the parameter  $\epsilon_y$ .

### 2.2.2 National electricity sector

Electricity  $N$  (for Nuclear) in our model is a consumption good for households ( $N^h$ ) and an intermediary input for firms ( $N^y$ ). We assume electricity is produced competitively using capital  $k^N$  and fossil fuel  $F^N$ , according to the following program:

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

such that

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

### 2.2.3 Imported fossil fuel sector and the rest of the world

Fossil fuel is imported from the rest of the world, at a price  $p^F$  that reacts to the demand:

$$p^F = \bar{p} F^{\delta_F}$$

The rest of the world uses this revenue to import goods  $X$  from the domestic economic. The budget constraint of the rest of the world – or equivalently the equilibrium condition for the current account of both the domestic economy and the rest of the world – is then:

$$X = p^F F$$

This assumption is a reduced-form representation of the rest of the world, while still allowing fossil fuel prices to adjust following a decline in domestic demand.

### 2.2.4 Regional housing supply sector

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

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

where  $H_k$  is a constant and  $\delta_H$  is the price elasticity of housing supply.

## 2.3 Fiscal authority

The fiscal authority gets revenue from taxes on labor income, capital income, consumption and carbon taxation (i.e. fossil fuel consumption). It uses its revenue to

fund transfers ( $T$ ), public spending ( $G$ ) and public debt repayment ( $r_t \bar{d}$ ). Denoting  $\mu_t(a, z, k)$  the measure of households with state  $(a, z, k)$ , the aggregation over all households is given by  $X_t = \int x \, d\mu_t(a, z, k)$  for  $x \in \{a, c, F^h, N^h\}$ , and firms aggregation  $F_t^Y = \sum_k F_{k,t}^Y$ . The government has the following budget constraint:

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

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

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

Apart for the carbon tax revenue, the budget constraint clears with  $G$ . However, the carbon tax revenue can be separately allocated either to finance an increase in public spending, or to fund lump-sum transfers towards households, possibly contingent on income and location. We explore these different scenarios in [Section 5](#).

## 2.4 Market clearing conditions and equilibrium

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

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

Households' savings are claims on a mutual fund that holds capital, housing and public debt, and redistribute the average return to households according to the equation:  $r_t a_t = (r_t^K - \delta) K_t + \sum_k p_{k,t}^H H_t^k + r_t d_t$ . Note that in this model, we don't consider the specific valuation effects coming from the local housing market. This means that our Parisian households in the model do not own housing in Paris but rather own a share

of the total housing stock, proportional to their wealth. Therefore, our model might underestimate the gap between Paris and rural areas. After carbon taxes, Parisian households might benefit from an increase in housing prices. We leave that for future research.

The goods and services (G&S) production ( $Y$ ) is consumed by households ( $c$ ), government ( $G$ ) or foreigners ( $X$ ), or invested by firms ( $I^N, I_k^Y$ ), partly to compensate the depreciation rate, so that we have  $I_t = K_{t+1} - (1 - \delta)K_t$ . Electricity  $N$  is consumed as intermediate inputs by firms ( $N^Y$ ), or as a commodity good by households ( $N^h$ ).

We define the equilibrium as paths for households decisions  $\{C_t, H_t, N_t^h, F_t^h, A_{t+1}, K_{t+1}\}_t$ , G&S firm decisions  $\{Y_{k,t}, L_{k,t}^Y, K_{k,t}^Y, F_{k,t}^Y, N_{k,t}^Y\}_{k,t}$ , electricity firm decisions  $\{N_t, K_t^N, F_t^N\}_t$ , relative prices  $\{r_t, w_{k,t}, p_t^N\}_{k,t}$ , fiscal policies  $\{\Gamma(\cdot), \tau^k, \tau^{\text{VAT}}, \tau_t^h, \tau_t^f\}_t$ , public expenditures  $\{T_t, G_t\}_t$ , and aggregate quantities, such that, for every period  $t$ , (i) households and firms maximize their objective functions taking as given equilibrium prices and taxes, (ii) the government budget constraint holds, and (iii) all markets clear.

### 3 Calibration on French macro and micro data

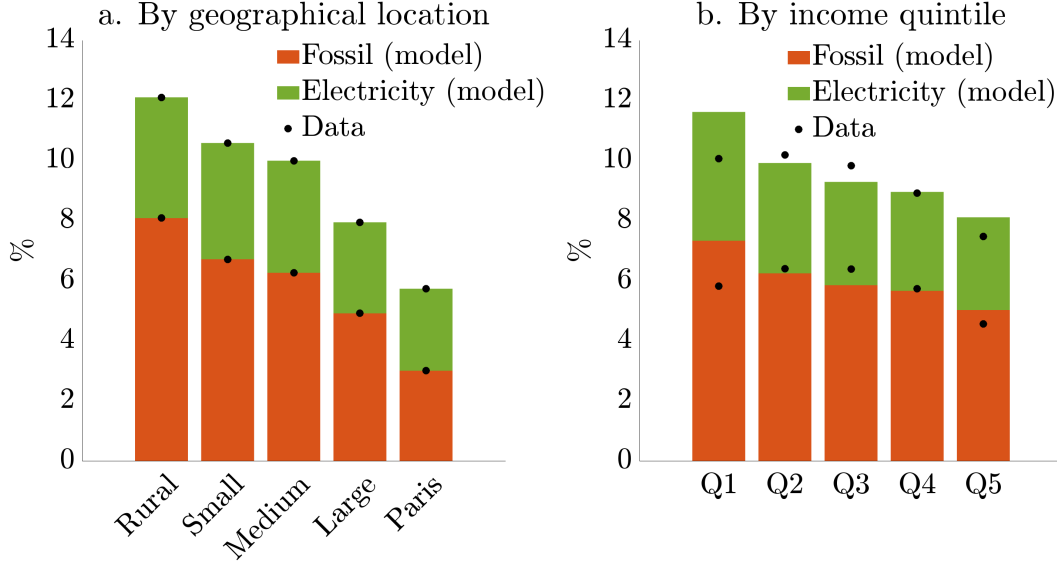
As this paper assesses the distributive effects of carbon taxation, the main point of the calibration is to reproduce the energy mix used by households and firms in France, along the geography and income dimension. As shown in Section 1, households in rural areas consume more energy and fossil fuel than households in large cities, and work in more emission-intensive firms. We carefully calibrate the joint geography-income distribution, the migration patterns between regions, and the main aggregates. As explained in Appendix B, our calibration strategy is to directly integrate parameters as guesses of the model, so that each aggregate target is precisely matched. In this section, we describe how we choose the target for each parameter. The values for all parameters are presented in Table 9. Untargeted moments – income composition, taxes, wealth and MPCs distributions – are presented in Appendix C.

#### 3.1 Households

**Consumption heterogeneity:** We use  $\Lambda_E$  and  $\Lambda_H$  to match the average energy and housing share in total expenditures, and we normalize  $\Lambda_C$  to 1 as in Comin, Lashkari and Mestieri (2021). The parameters  $\epsilon_E$  and  $\epsilon_H$  are calibrated to fit the non-homotheticity of energy and housing across the income distribution,  $\epsilon_C$  is normalized to 1. The parameters  $\{\epsilon_j\}_{j \in \{E,H\}}$  control relative income (expenditure) elasticities of demand across different goods. Let's denote the consumer's average non-homotheticity parameter  $\bar{\epsilon}_i = \sum_i \omega_{i,j} \epsilon_j$  with  $\omega_{i,j}$  the expenditure share in sector  $j$  for household  $i$ .

When  $\sigma \in (0, 1)$ , if  $\epsilon_j < \bar{\epsilon}_i$  this means that the good  $i$  is a necessity good for household  $j$  in the sense that it has an expenditure elasticity lower than 1. In our current calibration both energy and housing are considered as necessity goods for the average household.<sup>10</sup> We then add the  $\bar{e}(k)$  to match the observed spatial heterogeneity in energy constraints. We normalize  $\bar{e}(\text{Paris}) = 0$  and set the other  $\bar{e}(k)$  to match the average energy share in each city type, and  $\gamma(k)$  to have the right energy mix in each area, as shown in Figure 4.a.

Figure 4: Energy share in total consumption



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

**Source:** BdF 2017 Insee survey.

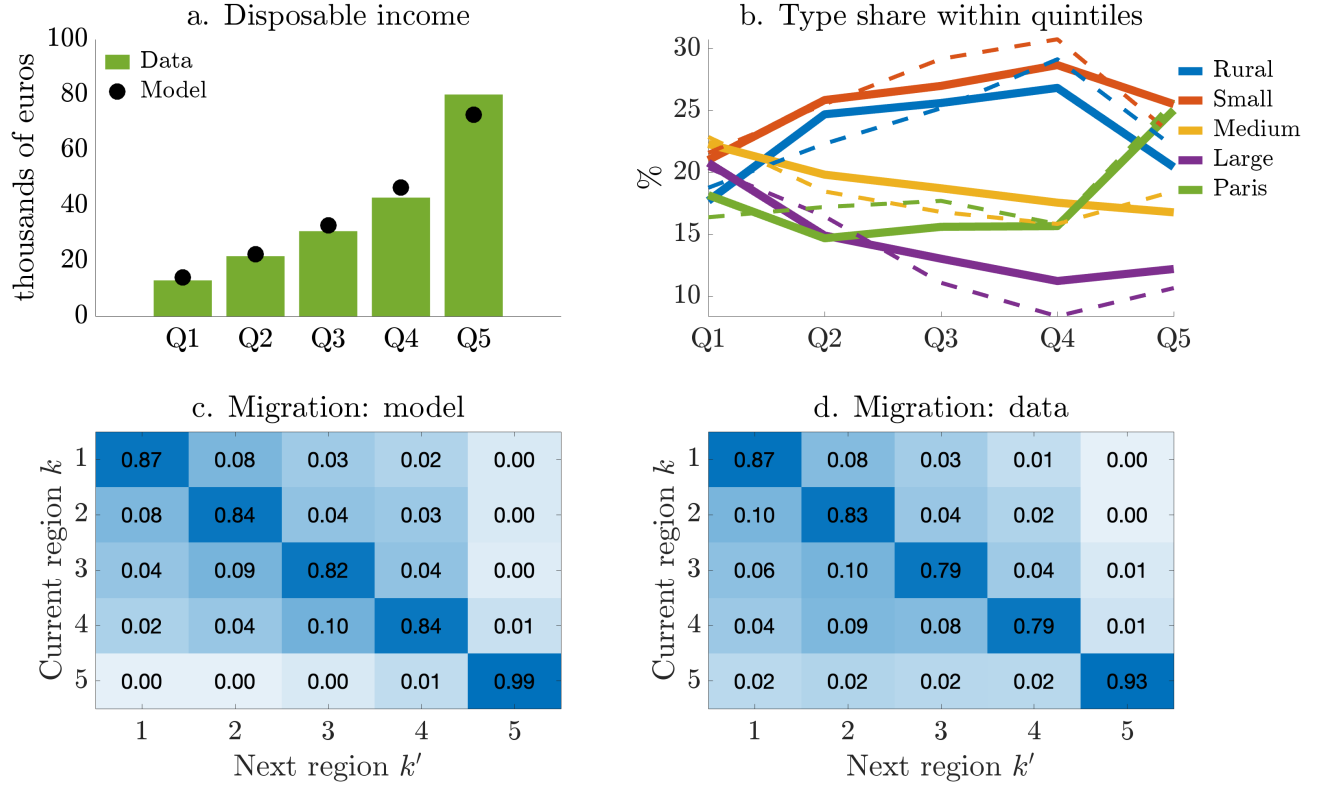
We estimate the elasticity of substitution between energy and G&S consumption to  $\sigma = 0.2$ , using National Accounts longitudinal data from 1959 to 2021 (the data and method are described in Appendix C). Finally, we set the elasticity of substitution between fossil fuel and electricity to  $\epsilon_h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

**Income process:** as changes in transfer, labor and capital incomes account for a

<sup>10</sup>Note that in a 3-good (or higher) environment, being a luxury or a necessity good is not an intrinsic characteristic of a good but depends on the consumer's income level.

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<sup>11</sup> (Figure 5.a), using the AR(1) persistence parameter  $\rho_z$ , which is set to be the same across all types. We use the means  $\mu_z(k)$  and variances  $\sigma_z(k)$  of the idiosyncratic productivity process for each type to match the proportion of each geographical location type within each disposable income quintile (Figure 5.b). Our model recovers that Parisian households are richer than average, as they account for 26% of the top income quintile but only 19% of the population. Households living in rural areas or small cities are more equally distributed, with over-representation in Q2, Q3 and Q4, and under-representation in Q1 and Q5.

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). Panels *c* and *d*: probability to have migrated from  $k$  towards  $k'$  5 years later, 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 BTS-Salariés 2016-2021.

**Migration and other parameters:** we compute the migration matrix between

<sup>11</sup>From the 2021 Insee survey “Revenus et patrimoine des ménages” (RPM 2021).

each region over 5 years<sup>12</sup>, *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  $5 \times 5$  migration cost matrix  $\kappa$  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). Finally, we set the annual discount factor  $\beta = 0.94$  to match the French capital-to-income ratio<sup>13</sup> 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 lie within the range of estimates from [Papageorgiou, Saam and Schulte \(2017\)](#): we provide robustness check for alternative values in Appendix F. The capital share is set to  $\alpha = 0.31$  to match the share of labor revenue  $\frac{wl}{\text{GDP}} = 65\%$  following [Cette, Koehl and Philippon \(2019\)](#). The share of fossil fuel in the policy mix is set to  $\gamma_y = 0.86$  such that electricity accounts for 33% of the regional firms' energy mix. Finally, the depreciation rate is set to  $\delta = 11.8\%$  to match the aggregate share of investment as in [Auray et al. \(2022\)](#).

**Electricity firm and other parameters:** the electricity sector is capital intensive, so we set  $\zeta = 0.9813$  to have  $\frac{F_N}{F} = 1\%$ . We assume that electricity is produced using few fossil fuel inputs because France relies mainly on nuclear power plants and hydroelectricity from dams. The initial price  $p^F$  of the imported fossil fuel is set such that fossil fuel imports account for 4% of the GDP. 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 ( $\delta^F = 0$ ):

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<sup>12</sup>To compute this migration matrix, we use the panel data BTS-Salariés 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.

<sup>13</sup>See 2022 [Banque de France report](#).



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). Following Auray et al. (2022),  $\lambda$  targets public spending  $\bar{G}$  at 29.3% of GDP, we set the effective VAT rate  $\tau^{\text{VAT}}$  to 22.24% and the effective capital income tax rate to 9.02%. The resulting amount of tax paid by each group of households is shown in Figure 11.b. The fit with the data is good, as we mostly miss corporate taxes in the model.

## 4 Quantitative results

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

*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  $\tau^h$  or  $\tau^f$ . 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. We assume the planner is able to anticipate all future reactions of agents (even migration) and will therefore set carbon taxes in order to reach its emissions target. The increase in tax is linear: the tax rises from 0 to  $\tau^{\text{final}}$  in 10 periods, and stays at  $\tau^{\text{final}}$  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: “what share of my income should I receive to be indifferent between staying at the initial steady state, or experiencing the transition?”. Formally, we retrieve  $x$  by computing for each initial wealth  $a_0$ , region  $k_0$  and productivity  $z_0$  the following equality:

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

with  $U = \frac{u^{1-\theta}}{1-\theta}$ . Finally, we express the wealth equivalent by dividing  $x$  by total disposable income:  $\text{WE}(a_0, k_0, z_0) = x(a_0, k_0, z_0) / \text{TI}(a_0, k_0, z_0)$ .<sup>14</sup> We then divide this number

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<sup>14</sup>With  $\text{TI}(a, k, z) = \Gamma(z(k)w(k)\bar{l}) + (1 - \tau^k)ra + T(k)$ .

by the following infinite sum  $\sum_{t=1}^{\infty} \beta^t \approx 15.7$ . This gives the transfer a household should receive *every year* in order to be indifferent between staying at the steady state, or experiencing the transition. Therefore, a wealth equivalent of  $-1\%$  means that a household should receive every period a lump-sum transfer equal to  $1\%$  of their initial income in order to be indifferent between staying at the steady state, or going through the transition with the increase in carbon tax.

In this section, we describe the transmission of  $\tau^h$  and  $\tau^f$  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

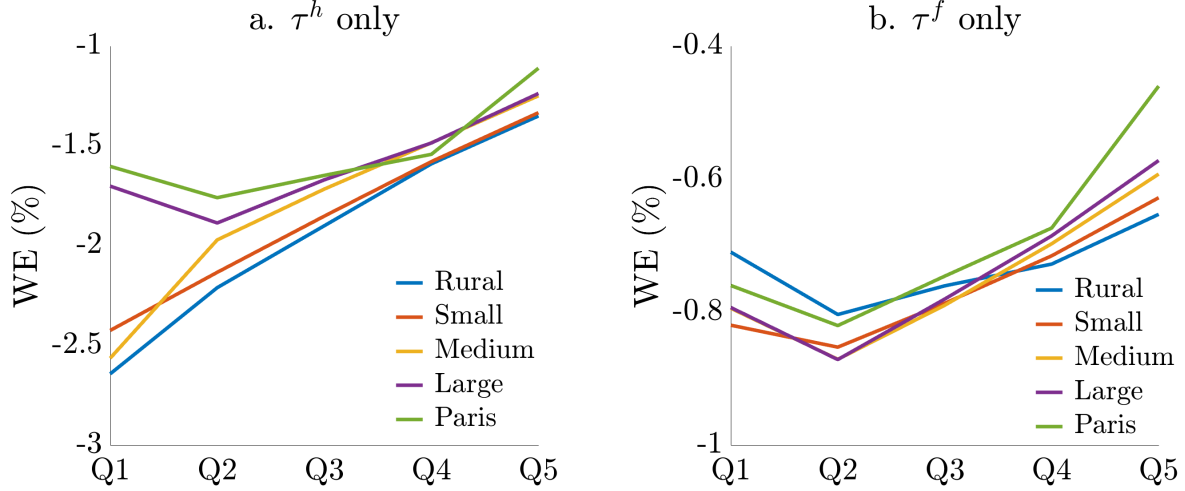
The carbon tax burden varies significantly depending on location, income, and the type of tax. Figure 6 presents the average welfare effects (in wealth equivalent, as described above) by region and income quintile for the initial distribution, for an increase of  $\tau^h$  only (left panel) and  $\tau^f$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

Before examining the different channels, we provide some general observations. First, there is a welfare cost associated with reducing emissions by  $10\%$ , as the WE is negative for all the groups considered. This outcome reflects our assumption that government expenditure  $G$  is not valued by households. However, public spending could contribute positively to well-being. Therefore, the net welfare impact of carbon taxation could potentially be welfare-enhancing. The extent of this effect hinges on the nature of the spending involved, a question which falls outside the scope of our current analysis. Second, this cost is higher for  $\tau^h$  ( $-1.7\%$  of initial disposable income on average) than for  $\tau^f$  ( $-0.7\%$  of initial disposable income). This implies that the social planner would need to compensate each individual with €673 every year to make households accept the increase in  $\tau^h$ , and €272 for the increase in  $\tau^f$ .<sup>15</sup> Third, both taxes are regressive, as the welfare cost is higher for poorer households. The regressive effect is significantly more pronounced for  $\tau^h$ . Fourth, 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.

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<sup>15</sup>Our policy experiments correspond to an increase in  $\tau^h$  of €149 per tCO<sub>2</sub>, and an increase in  $\tau^f$  of €117 per tCO<sub>2</sub>. They would represent a one-time equivalent transfer of €10,500 for  $\tau^h$  and of €4,250 for  $\tau^f$

Figure 6: Welfare effect by region and income



*Carbon tax on households ( $\tau^h$ ).* 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  $\tau^h$  depends on two key factors: the direct effect of the carbon tax and the change in rents  $p^H$ . The direct effect of  $\tau^h$  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 ( $\epsilon_E$ ) and geography ( $\bar{e}$ ) generates heterogeneous welfare costs. Specifically, the welfare cost is equal to  $-1.9\%$  of initial disposable income (WE) in rural areas compared to  $-1.5\%$  WE in the Parisian agglomeration, and  $-2.2\%$  WE for the bottom income quintile (Q1) versus  $-1.2\%$  WE for the top quintile (Q5). However, this adverse effect on rural households is partially offset by a decline in rents. 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 the Parisian agglomeration, 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 ( $\tau^f$ ).* 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  $\tau^f$  depends on adjustments in wages, housing rents, and the interest rate. Since firms in rural areas are more fossil fuel-intensive, the rise in fossil fuel prices reduces the demand for other inputs, particularly labor, leading to a decrease in wages of  $3.9\%$  in rural areas compared to  $1.1\%$  in the Parisian agglomeration. This results in welfare costs of  $-1.1\%$  WE and  $-0.3\%$  WE,

respectively. The decline in wages disproportionately affects lower-income households, as labor income constitutes a larger share of their total income. As with  $\tau^h$ , this geographic burden is partially offset by a decrease in rents: as households migrate from rural areas to urban areas for better wages,  $p^H$  decreases in rural areas, mitigating losses 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.

*Policy implication of EU-ETS 1 and EU-ETS 2.* While not entirely similar, our framework can give us insights on the expected effects of the European Union Emissions Trading System (EU ETS). The first scheme (EU-ETS 1), introduced in 2005 and targeting specific industrial sectors, corresponds to our tax on firms, denoted as  $\tau^f$ . In contrast, the upcoming extension (EU-ETS 2, also known as Phase 4), scheduled for 2027 and covering sectors not included in the initial phase – primarily goods directly consumed by households – aligns closely with our tax on households,  $\tau^h$ . In Figure 6, we set  $\tau^h$  or  $\tau^f$  such that, at the final steady state, total emissions are reduced by 10% compared to the initial steady state. This represents a carbon tax increase by €149 per tons of CO<sub>2</sub>eq for households, and €117 for firms.<sup>16</sup> Our simulations show that the emission and welfare responses are linear with respect to tax levels, with negligible interactions between  $\tau^h$  and  $\tau^f$ . Therefore, we can extrapolate our results for different price combinations of the EU-ETS schemes. At the peak of the EU-ETS1 in 2023, the price of a ton of CO<sub>2</sub> reached €100, which translates into an 8.5% decrease in total emissions, provided that EU-ETS1 covers all direct emissions by firms. For the future EU-ETS2, the first three years will include a price containment mechanism, whereby if the price exceeds €45, additional allowances may be released. This maximal price translates into a 3% decrease in total emissions, provided the EU-ETS2 extension covers all direct households emissions. Therefore, assuming a price of €100 for both the current EU-ETS and its extension, and providing they cover all direct emissions from both firms and households, our model predicts a decline of 15% in total emissions, and a welfare cost equal to −1.8% of initial disposable income (or €−629).

*Robustness checks.* Our primary objective is to quantify the redistributive effects of carbon taxes. To this end, we have calibrated the model using relatively low elasticities of substitution, reflecting limited short-run adaptability. In Appendix F, we replicate the main experiments using alternative values for key elasticities ( $\sigma$ ,  $\sigma_y$ ,  $\epsilon_y$ ,  $\epsilon_h$ ). We find that the distributional results are largely robust to changes in  $\sigma_y$ ,  $\epsilon_y$ , and  $\delta_H$ : average welfare losses remain around −1.05% (in wealth equivalent terms), with rural

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<sup>16</sup>As firms emit more and have a higher elasticity of substitution for clean energy, they require lower taxes to reduce emissions by the same amount.

households experiencing losses approximately 18% higher than those in the Parisian agglomeration, and households in the bottom income quintile (Q1) facing welfare losses 45% higher than those in the top quintile (Q5). The elasticity of substitution between fossil fuels and electricity for households ( $\epsilon_h$ ) plays a somewhat more significant role. Reducing  $\epsilon_h$  from 1.5 to 1.3 increases overall welfare losses by 0.21 point, as it becomes harder to substitute away from fossil energy. The rural/Paris welfare gap also widens slightly, from 18.1% to 18.8%, reflecting rural households' higher reliance on fossil energy. The most influential parameter is  $\sigma$ , the elasticity of substitution between energy and other consumption goods. Increasing  $\sigma$  from 0.2 to 0.4 halves the average welfare cost of carbon taxation and significantly reduces the rural/Paris disparity. As energy becomes more easily substitutable, differences in baseline energy consumption matter less for welfare outcomes. These findings suggest that long-run calibrations, featuring greater flexibility and substitution possibilities, may yield different results. They also highlight that the political acceptability of carbon taxation could be enhanced through policies that facilitate adaptation, such as promoting electric vehicles, improving public transportation, and investing in energy-efficient housing.

In conclusion, due to differences in households' energy consumption baskets for  $\tau^h$  and firms' fossil fuel intensity for  $\tau^f$ , both carbon taxes disproportionately impact rural areas and lower-income households. Migration and housing price adjustments partially mitigate the welfare costs along the geographic dimension. In the following section, we further examine the role of migration and the welfare costs over different time horizons.

## 4.2 Migration and welfare

In our spatial model, households can migrate subject to a migration cost  $\kappa$ , 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 (keeping the same target of - 10% in total emissions) but restrict households from migrating (formally, we set  $\kappa = \infty$ ). The blue bars represent the results of our benchmark with migration, while the black dashed line reflects the scenario without migration. We observe that, although migration does not significantly affect welfare costs across the income dimension, it substantially reduces disparities along the geographical dimension. Without migration, rural areas face welfare costs equal to -2.7% WE of initial disposable income for  $\tau^h$  and -1.2% WE for  $\tau^f$ , compared to -1.9% WE and -0.8% WE with migration. The opposite effect is observed in large cities: they attract households from rural areas seeking to avoid the carbon tax, which pushes housing rents up, and real wages down. Therefore, welfare costs in the Parisian agglomeration are

significantly higher with migration than without.

These results highlight the critical role of migration in shaping the distributional effects of carbon taxes. In Figure 15 in Appendix, we illustrate population changes between steady states across income and geographic dimensions. For both taxes, significant composition effects occur within each region, but they are very different for  $\tau^h$  and  $\tau^f$ . Under  $\tau^h$ , the increase in energy price tends to incentivize poor households to move away from rural areas and small cities, and they are replaced by richer households who can support the increase in prices: in the new steady state, average household income increases by 2.4% in rural areas and 1.1% in small cities relative to the initial steady state, but falls by 3% in large cities, highlighting interregional recomposition effects. The composition effect is reversed for  $\tau^f$ . As wages decline by 4% in small cities against only 1% in the Parisian agglomeration, high-productivity workers migrate from small to large cities. They are replaced by low-productivity households for which this change is less important, as a more substantial fraction of their consumption is financed by transfers. 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.

For more details about the dynamics of the model, we plot the difference between the mobility matrix at several periods during the transition and the mobility matrix of the initial steady state in Figures 16 and 17.

*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:

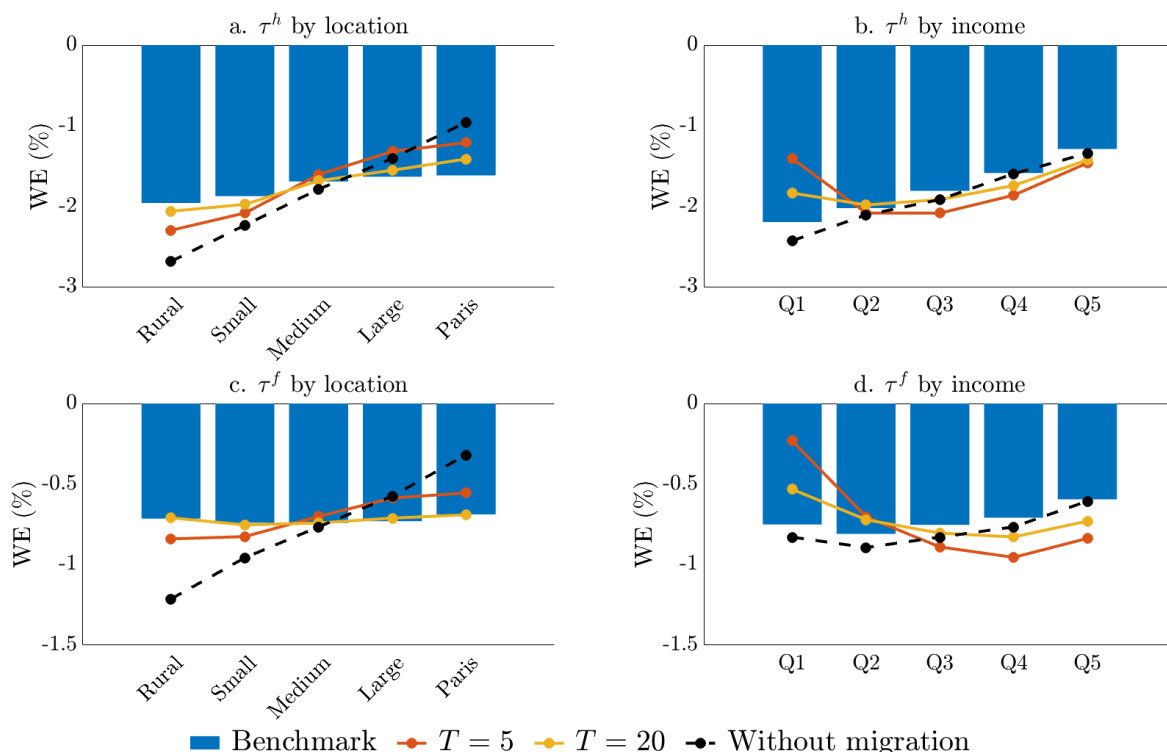
$$\sum_{t=0}^T \beta^t \mathbb{E}_0[U_{i,t}^{\text{no tax}} | a_0 + x, k_0, z_0] = \sum_{t=0}^T \beta^t \mathbb{E}_0[U_{i,t}^{\text{tax}} | a_0, k_0, z_0]$$

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  $T = 5$  years and  $T = 20$  years, while the blue bars correspond to  $T = \infty$ . As shown, the distributive effects differ significantly between the short run and the long run. At  $T = 5$ , 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 fully materialized, the cost of  $\tau^h$  and  $\tau^f$  are concentrated in the middle of the income distribution, as illustrated by the horizon-5 decomposition in Figure 14. This “U-shape” pattern aligns with panel *b* of Figure 5, which shows that rural households are concentrated in the middle of the income distribution, whereas Parisian households are concentrated at the tails. Another reason for this U-shape is the fact that the real interest rate decreases a lot in the first periods, hurting less low-income households.

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



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% ex-post reduction in emissions between the initial and final steady states. We assume both taxes are equal, *i.e.*  $\tau^h = \tau^f$  (in Appendix E, we also consider scenarios with  $\tau^h \neq \tau^f$ ). The transfer rule in each scenario is the following<sup>17</sup>:

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

where  $T$  is the transfer,  $y_i$  the total household's income, CTR the carbon tax revenue, and  $\mu$  the scaling parameter<sup>18</sup>.

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<sup>19</sup> of  $x$  to maximize welfare, as defined in Section 4. This scenario assumes the government knows household income and can implement a progressive transfer (if  $x > 0$ ) but cannot differentiate based on location  $k$  (or is legally restricted from doing so, as in France). Finally, in the “**Income  $\times$  Geography**” scenario, we optimize over five different  $x_k$ , allowing the government to apply region-specific progressivity levels.

<sup>17</sup>We also computed results for the additive rule  $T(y, k) = (x_k + y^{-x}) \cdot \text{CTR} \cdot \mu$ , but found that it yields a lower welfare than scenario 4. Moreover, in Appendix E, we consider an alternative rule to account for progressivity.

<sup>18</sup>Total income:  $y = \Gamma(zwl) + (1 - \tau^k)ra + \bar{T}$ . Carbon tax revenue:  $\text{CTR} = \tau^h(1 + \tau^{\text{VAT}})F^h + \tau^f(F^y + F^N)$ . Scaling parameter:  $\mu = 1 / \int_i y_i^{-x_k}$ .

<sup>19</sup>Scenario 3:  $x = 2.15$ . Scenario 4:  $x_k = [2.07, 2.08, 2.38, 2.4, 2.27]$ .



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.

Table 2: Median welfare by location and income

|     | Scenario                  | Rural | Small | Medium | Large | Paris | All   |
|-----|---------------------------|-------|-------|--------|-------|-------|-------|
| (1) | Benchmark $G$             | -1.10 | -1.11 | -0.98  | -0.98 | -0.93 | -1.03 |
| (2) | Uniform                   | 0.41  | 0.43  | 0.50   | 0.66  | 0.47  | 0.47  |
| (3) | Income                    | 0.48  | 0.48  | 0.64   | 0.85  | 0.66  | 0.60  |
| (4) | Income $\times$ Geography | 0.48  | 0.50  | 0.86   | 1.54  | 0.75  | 0.64  |
|     |                           | Q1    | Q2    | Q3     | Q4    | Q5    | All   |
| (1) | Benchmark $G$             | -1.16 | -1.22 | -1.13  | -0.98 | -0.82 | -1.03 |
| (2) | Uniform                   | 1.30  | 0.80  | 0.46   | 0.19  | 0.06  | 0.47  |
| (3) | Income                    | 4.26  | 1.69  | 0.40   | -0.13 | -0.04 | 0.60  |
| (4) | Income $\times$ Geography | 6.05  | 2.02  | 0.48   | -0.08 | 0.01  | 0.64  |

**Notes:** Welfare is computed as wealth equivalent (in % of households’ disposable income) over the transition.

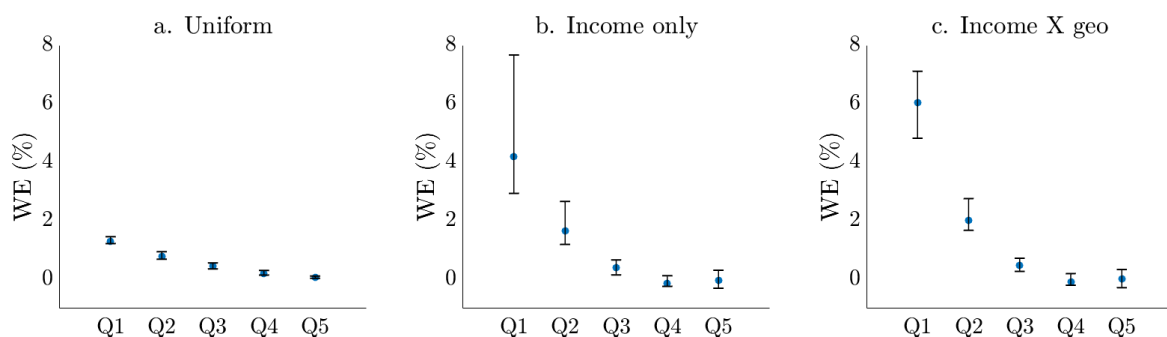
Our benchmark scenario yields welfare losses, as the revenue is used to increase  $G$  that is not valued by households. This is the most natural choice to study the distributive effects of carbon taxation, as introducing  $G$  in the utility function would directly affect inequality and distort the analysis. Therefore, replacing this inefficient use of carbon tax revenue with a uniform transfer naturally yields a higher utility: the comparison is more relevant for the distributive effects, and the welfare ratios between areas or income quintiles. Moreover, for our calibration, transfers are welfare-improving: a uniform transfer policy increases median welfare by 0.47% (WE), compared to the baseline scenario, without carbon tax.. As transfers redistribute resources from high-income households with low marginal utility to low-income households with high marginal utility, they increase aggregate utilitarian welfare (in Appendix E, we also use Negishi weights to neutralize the redistribution motive). Additionally, they mitigate inefficiencies arising from the borrowing constraint by providing some insurance to low-income households, which further increases welfare. Hence, the welfare gains stem from the model’s baseline calibration, and the relevant comparison is between our different transfer scenarios, not between  $T$  and  $G$ .

While a uniform transfer increases median welfare, an optimal progressive transfer targeting low-income households yields a 0.13 point higher welfare gain (+0.60% WE), at the expense of high-income groups. However, as illustrated in Table 14 in

the Appendix, the “**Income**” scenario 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  $\times$  Geography**” scenario, which allows transfer progressivity to vary by region. Relative to the income-only rule, this policy improves welfare by increasing progressivity in large cities and reducing it in rural areas and small towns. It raises median welfare across all income and geographic groups and reduces the share of households experiencing welfare losses by 10 percentage points compared to the income-only scenario. These gains stem from the fact that rural households are concentrated around the middle of the income distribution, whereas the lowest- and highest-income households are overrepresented in large urban areas. Allowing for region-specific progressivity better aligns transfers with local income profiles and reduces the dispersion of welfare gains. Figure 8 presents the 25th, 50th and 75th percentiles of the welfare gain distribution within each income quintile. Compared to the income-only policy, the Income  $\times$  Geography rule notably reduces the dispersion of welfare gains within the bottom quintile (Q1). As a result, **incorporating geography into redistribution policies improves median welfare by 0.04 point** (and average welfare by 0.13 point) relative to the optimal transfer based solely on income. This implies that compared to the uniform scenario, targeting both income and geographic criteria increases median welfare gains by one third more than targeting income alone. Note that this has no effect on median welfare in rural areas but it redistributes gains toward medium and high income within rural areas.

Figure 8: Median and quartiles of welfare gains by income quintile



**Notes:** This represents the median, top and bottom quartiles of welfare change for each income quintile over the transition. Welfare change are computed as a wealth-equivalent expressed in % of households’ disposable income.

As shown in Figure 18 in the Appendix, our different rebating rules yield different migration and composition effects across income groups and regions. In the “**Income**” scenario, many high-income households migrate from rural and small areas to medium

and large cities, while lower-income households move in the opposite direction due to declining rents. In contrast, this effect is mitigated in the “**Income  $\times$  Geography**” scenario: since transfers are less progressive in rural and small areas and more progressive in medium and large cities, rich households from rural areas and poor households from urban regions have fewer incentives to migrate.

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

## 6 Conclusion

In this paper, we study the distributive effects of carbon taxation with a focus on spatial heterogeneity. Using both household-level and matched employer-employee data from France, we document that rural households have a fossil fuel consumption share 2.8 times higher than urban households and are employed in firms that emit 2.7 times more. These patterns are consistent across other countries. We incorporate these findings into a spatial-heterogeneous agent model, featuring idiosyncratic income risks, endogenous 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, that depends on consumption of energy, housing, other goods and on migration costs, by 0.04 point, a result that holds across different welfare criteria and rebate schemes. Note that welfare costs of carbon taxes decrease with  $\sigma$  because it significantly reduces households’ energy share. 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, with possibly endogenous and directed technical progress. Additionally, our findings indicate that different forms of carbon taxation generate distinct migration responses, highlighting the need for further empirical research. A related point is sectoral reallocation of labor and capital. Transitions across zones often imply changes in sectoral employment and require skill adjustments, which can create significant frictions and distributional impacts. Addressing these would require introducing sectoral heterogeneity and modeling the dynamics of skill adaptation.

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# Appendix

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## A Descriptive Evidence

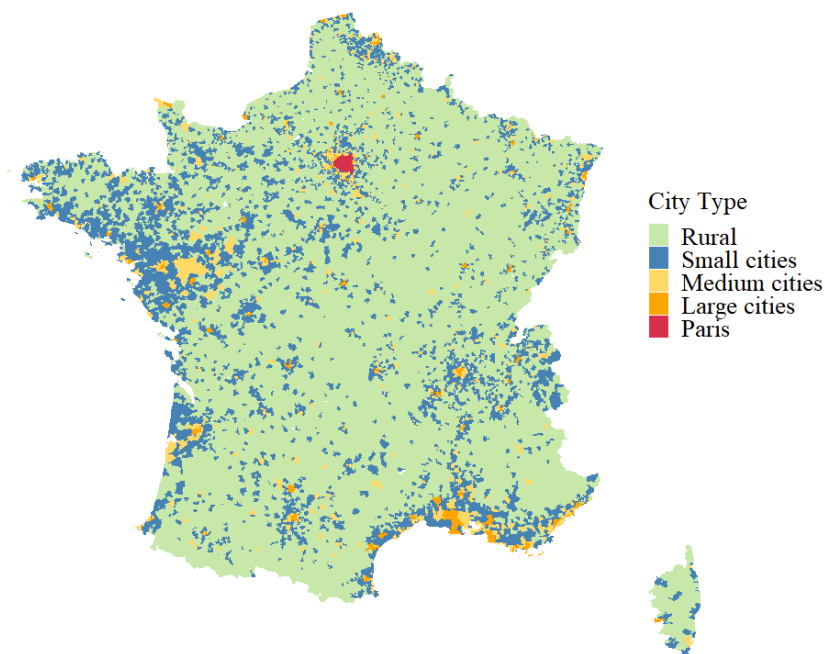
### A.1 City types

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 or urban unit of Paris, including the departments 75, 92, 93, and 94. The list of city codes is provided by [Insee](#)

We favor this categorization because the population is uniformly distributed across these locations, according to the latest 2021 French Census. We check that we recover a similar distribution in our administrative datasets used in the following sections (BTS and fiscal declarations from households). Figure 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   |
| <i>energy for housing</i>        | 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 |
| <i>energy for transports</i>     | 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  |
| <i>energy for housing</i>    | 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 |
| <i>energy for transports</i> | 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 |
|-----------|-------|-------|--------|-------|-------|
| <b>Q1</b> | 93.4  | 78.8  | 68.1   | 61.6  | 53.1  |
| <b>Q2</b> | 96.3  | 82.9  | 71.2   | 64.4  | 56.0  |
| <b>Q3</b> | 102.0 | 90.6  | 77.6   | 69.6  | 57.4  |
| <b>Q4</b> | 110.0 | 99.8  | 85.7   | 77.4  | 60.5  |
| <b>Q5</b> | 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 use Insee national accounts that reports total emissions and emissions per euro of value-added for most sub-sectors of the French economy. As a robustness, we also compute emissions intensity using datasets from Bach et al. (2024) (mining and manufacturing), CITEPA (waste). We build a  $tCO_2eq$  per worker metric using annual value-added and employment levels from 2022 Insee National Accounts. We find very heterogeneous results across sectors. Within manufacturing, ‘Coke & refining’ is the most intensive in emissions with 1,512  $tCO_2eq$  annual emissions per worker. ‘Air transports’ is the most intensive across all sectors with 2,379  $tCO_2eq$  per worker. In the services (except construction and transportation), firms emit on average 1.9  $tCO_2eq$  per worker. A notable exception among the services are ‘Rental and leasing activities’ that emits 43.7  $tCO_2eq$  per worker every year.

**Administrative data on workers and firms.** *All employer - employee data*

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

**Merging BTS micro data and sectoral emissions.** From the BTS 2022, we assign to each worker  $i$  the average emissions intensity from its firm’s  $f$  i.e.  $\alpha_i = \alpha_f$ . In each group (city or quintile), we then compute the average  $\alpha_i$  i.e.  $\frac{1}{\text{length}(q)} \sum_{i \in q} \alpha_i$ . Those results are presented in Figure 2. For our extensive margin, we define emissions-intensive sectors as those with a tCO<sub>2</sub>eq per worker above 5. This represents the 20% most emissions-intensive jobs. We additionally report the share of workers in those sectors in Table 6 and Table 7.

Table 6: Share of workers (%) in each sector, by geography and income quintile

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

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

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

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

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

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

## A.4 Predicted energy shares and emissions

**OLS 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:

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

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<sup>20</sup> and average emissions per worker in

<sup>20</sup>The displayed values are equal to the coefficients, plus a constant to obtain the right average.

Figure 2. As a robustness, we use different estimates of sectoral level emissions from [Bach et al. \(2024\)](#) and the CITEPA in column (5), while column (4) uses sectoral-level estimates from national accounts. In both columns, we used the sector of the establishment since the biggest firms may operate in several sectors with different emissions intensities. As an additional robustness check, we also provide the same regressions using firm-level sectoral emissions in column (6).

Table 8: Regressions

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

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

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



## B Algorithm

The main challenges of this paper are the heterogeneous-agent structure, the discrete location choice and the high number of guesses. In this section, we detail the algorithms used at the steady state, for the calibration and during the transition. Each steady state takes 5 seconds to compute on a personal computer, and 27 seconds for a non-linear transition between two distinct steady states. The entire code has been written from scratch on Matlab.

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

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

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

- **a**: for the household's decision  $a'(a, k, z)$ , we put  $a'$  on our grid  $\mathbb{A}$ , by computing weights  $\omega^-$  and  $\omega^+$  depending on the distance between  $a'$  and the inferior ( $a^-$ )

and superior ( $a^+$ ) points of the grid, and we put the values  $\omega^-$  and  $\omega^+$  at every rows  $a^-$  and  $a^+$  of the state space.

- **z:** using the Tauchen weights, we put the probability  $P(z \rightarrow z')$  at every rows  $z'$ .
- **k:** using the migration probability  $\mathbb{P}(k \rightarrow k')$  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  $\vec{\epsilon} = \{\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4, \epsilon_5\}$ . Then the complete value function is the expectation of all  $k'$ -value function, taken over  $\vec{\epsilon}$ :

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

where the last equality derives from assuming that  $\epsilon_{k'}$  follows a Gumbel distribution with variance  $\varrho$  – 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 rents  $\{p_1^H, p_2^H, p_3^H, p_4^H, p_5^H\}$  (segmented housing markets), local outputs  $\{Y_1, Y_2, Y_3, Y_4, Y_5\}$  (segmented labor markets), and carbon tax revenue  $CTR$  (government budget constraint). For the calibration procedure, we use more than 30 guesses, as we add parameters as guesses and calibration targets as clearing conditions.

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

1. guess an initial vector  $\mathbf{x}_0$ , and compute the error  $\mathbf{e}_0 = f(\mathbf{x}_0)$ .
2. for each guess  $i$ , create the vector  $\mathbf{x}_0^i$  with  $\mathbf{x}_0^i(i) = \mathbf{x}_0(i) + \epsilon$  (with  $\epsilon = 10^{-4}$ ) and  $\mathbf{x}_0^i(\bar{i}) = \mathbf{x}_0(\bar{i})$ , and compute the error  $\mathbf{e}_0^i = f(\mathbf{x}_0^i)$ .
3. create the Jacobian matrix  $M$  of size  $n_g^2$  that relates a change of each guess to a change in each clearing condition. The column  $i$  is the vector  $\mathbf{e}_0^i - \mathbf{e}_0$ .
4. iterate the guess using  $\mathbf{x}^{new} = \mathbf{x} + \alpha$ , with  $\alpha = -M^{-1} * \mathbf{e} * d$ , with  $d$  a dampening factor (usually equal to 1, can be lower if the initial guess is far for the equilibrium). Denote  $\mathbf{e}^{last} = \mathbf{e}$  the error.
5. compute  $\mathbf{e}^{new} = f(\mathbf{x}^{new})$ .
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  $t^{shock}$  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                                       |
|-------------------------|-------------------------------|--------------------------------------|---------------------------------------------------------|
| <b>Households</b>       |                               |                                      |                                                         |
| $\beta$                 | Discount factor               | 0.94                                 | $\frac{a}{GDP} = 4.5$                                   |
| $\theta$                | Intertemporal ES              | 1                                    | Kaplan, Moll and Violante (2018)                        |
| $\sigma$                | ES between $c$ and $e^h$      | 0.2                                  | Estimated in Appendix C                                 |
| $\Lambda_E$             | Energy share                  | 0.095                                | Energy share in consumption = 9.5%                      |
| $\Lambda_H$             | Housing rents share           | 1.464                                | Housing spending share in consumption = 17%             |
| $\epsilon_E$            | Non-homotheticity parameter   | 0.9                                  | Energy expenditures across income quintiles             |
| $\epsilon_H$            | Non-homotheticity parameter   | 0.25                                 | Housing expenditures across income quintiles            |
| $\Lambda_C, \epsilon_C$ | 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              |
| $\epsilon_h$            | 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                               |
| $\rho_G$                | Gumbel shock variance         | 0.1                                  | Income heterogeneity, aggregate                         |
| $\rho_z$                | 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                                         |
| <b>Firms</b>            |                               |                                      |                                                         |
| $p^F$                   | 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          |
| $\sigma_y$              | ES between $e^y$ and $(K, l)$ | 0.05                                 | Fried (2018)                                            |
| $\alpha$                | Capital share                 | 0.3089                               | $\frac{wl}{GDP}$ from Cetto, Koehl and Philippon (2019) |
| $\gamma_y$              | Share of fossil in Y mix      | 0.86                                 | Firms' share in total emissions = 62.5%                 |
| $\epsilon_y$            | ES between $F^y$ and $N^y$    | 1.5                                  | Fried (2018)                                            |
| <b>Government</b>       |                               |                                      |                                                         |
| $\bar{T}$               | Transfers                     | 0.08                                 | Share of $T$ in income                                  |
| $\tau$                  | Labor tax progressivity       | 0.08                                 | From Ferriere et al. (2023)                             |
| $\lambda$               | Labor tax level               | 0.571                                | $\frac{\bar{G}}{GDP} = 0.29$ as in Auray et al. (2022)  |
| $\tau^k$                | Corporate income tax rate     | 9.02%                                | Effective rate in Auray et al. (2022)                   |
| $\tau^{VAT}$            | 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 |
|----------------------|------|------|-------|------|------|------|
| <b>Rural</b>         | 17.7 | 24.7 | 25.6  | 26.8 | 20.4 | 23.5 |
| <b>Small cities</b>  | 21.0 | 25.9 | 27.0  | 28.7 | 25.5 | 26.0 |
| <b>Medium cities</b> | 22.3 | 19.8 | 18.7  | 17.6 | 16.8 | 18.5 |
| <b>Large cities</b>  | 20.8 | 14.9 | 13.05 | 11.3 | 12.2 | 13.4 |
| <b>Paris</b>         | 18.2 | 14.7 | 15.6  | 15.7 | 25.0 | 18.5 |
| <b>Sum</b>           | 100  | 100  | 100   | 100  | 100  | 100  |

For Figure 11, we use the *Revenus et patrimoine des ménages, Édition 2021*, that we reproduce below:

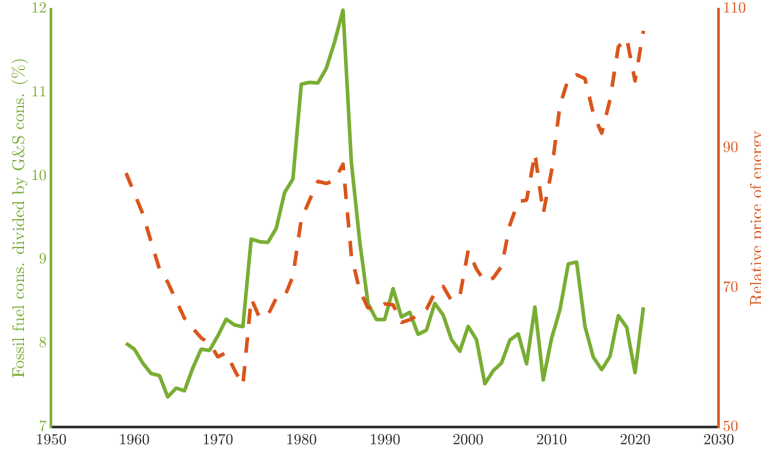
Table 11: Revenues and taxes by income decile (thousand euros)

|                                  | D1   | D2   | D3   | D4   | D5   | D6    | D7    | D8    | D9    | D10   |
|----------------------------------|------|------|------|------|------|-------|-------|-------|-------|-------|
| <b>Primary income</b>            | 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  |
| <b>Sum of taxes</b>              | -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 $\sigma$

In Figure 10, we use French longitudinal aggregate data taken from Insee 2022 national accounts. As explained in *Hassler, Krusell and Olovsson (2021)*, the share of energy in total consumption comoves with the relative price of energy. This would not happen if energy and goods consumption were perfect substitutes.

Figure 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  $\sigma$  through a simple OLS estimation:

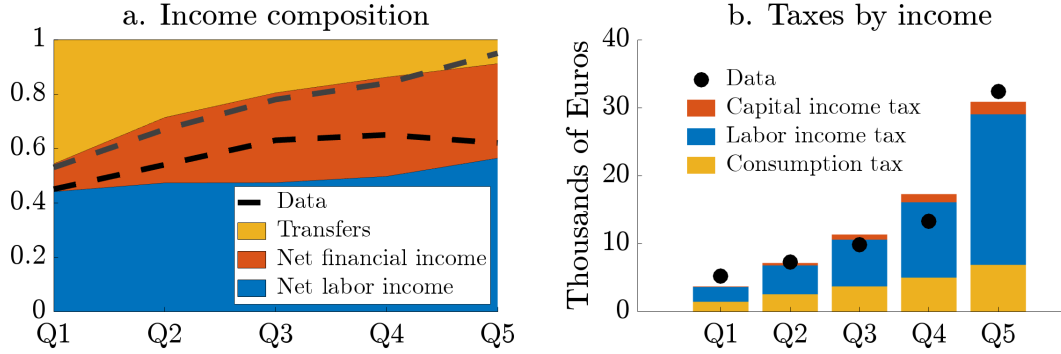
$$\Delta \ln(e_t^h) - \Delta \ln(c_t) = -\sigma \Delta \ln(p_t^h) + \epsilon_t$$

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

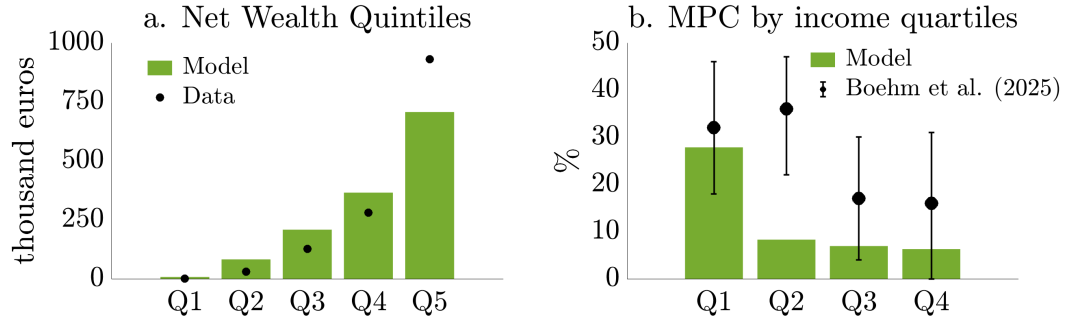


**Notes:** Panel *a*: composition of income data and model fit. Panel *b*: taxes paid by households in the model and data (excluding social contribution).

**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  $\tau^h$  and  $\tau^f$  into the 5 variables that affect directly households' budget constraint: wages ( $w$ ), household carbon tax ( $\tau^h$ ), electricity price ( $p^N$ ), interest rate ( $R$ ) and housing rents ( $p^H$ ). To obtain this decomposition, we start from the transition path, and we shut one variable at a time by setting its value to the steady state level. The effect we attribute to each variable is the difference between the total effect (with all variables moving along the transition) and the partial transition (with all variables moving, except one).

Figure 13: Decomposition of the welfare effect

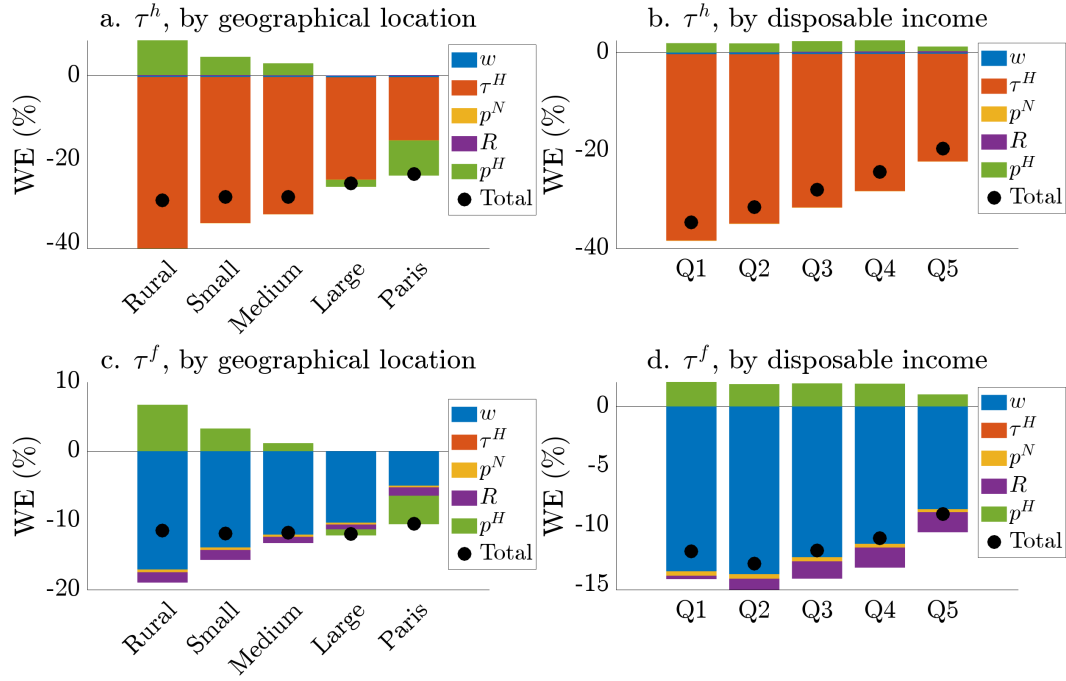




Figure 14 is the same decomposition, but considering only the welfare changes during the first 5 periods of the transition.

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

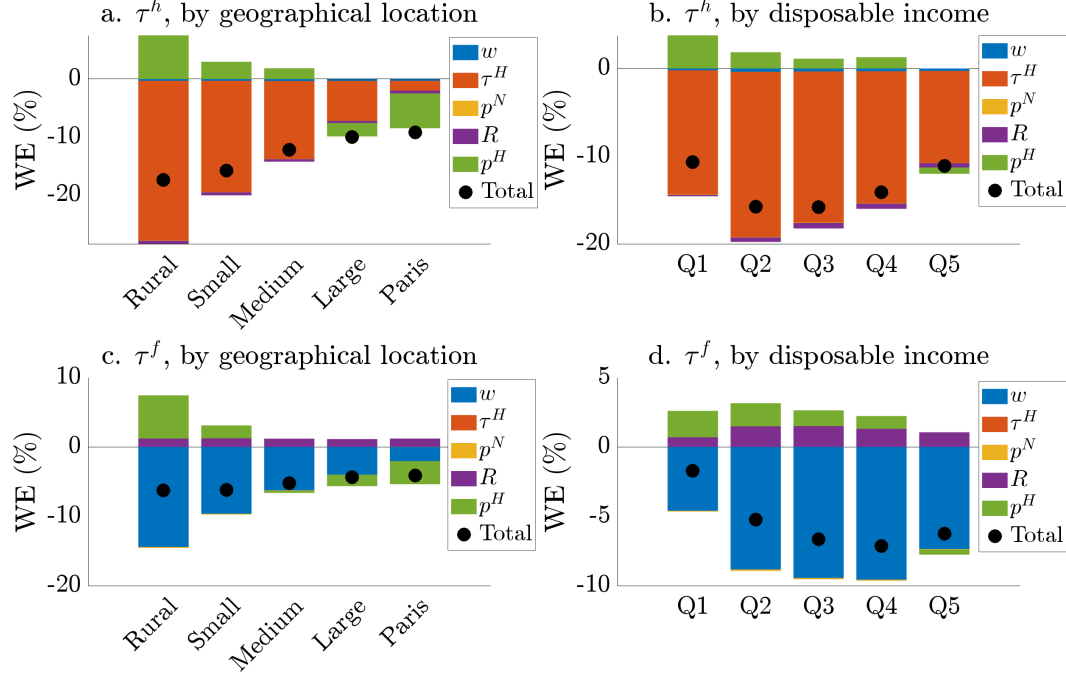
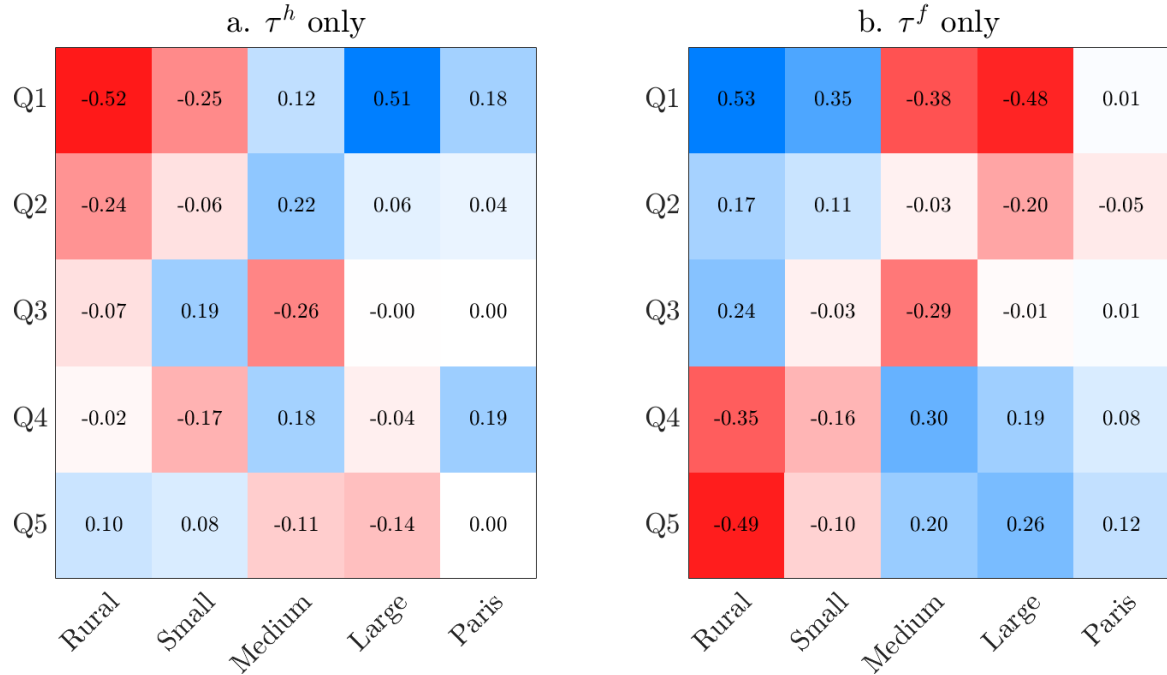


Figure 15 shows, for each group area  $\times$  income quintile, the change in population between the two steady states. The weighted sum of each line is equal to 0, as the share of households in each disposable income quintile is always 20% but the share of households within each region is not; the sum of each column can be different from 0, as households migrate between regions.

Figure 15: Density change by income and region between steady states

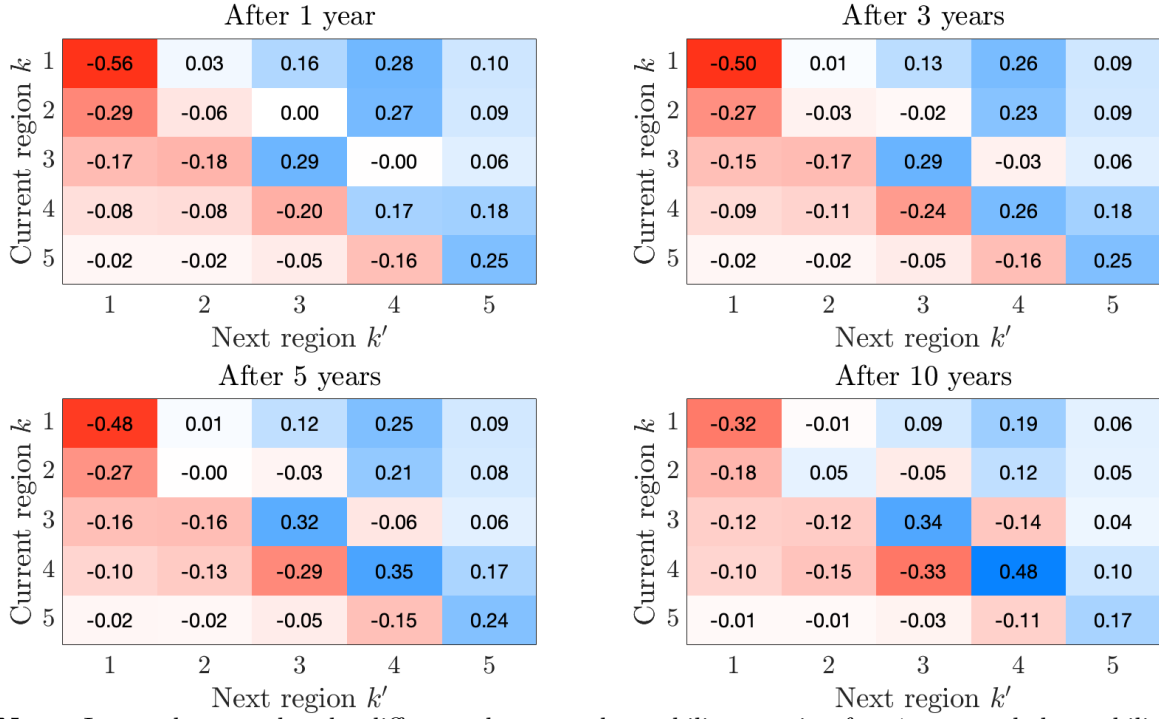


**Notes:** Panel *a*: only increase  $\tau^h$  with a 10% decrease in total emissions. Panel *b*: only increase  $\tau^f$  with a 10% decrease in total emissions. Disposable income quintiles are built at the national level.

**Lecture:** After the increase in  $\tau^h$ , in the new steady state, the share of households that are in rural areas and in the 1st quintile decreases by 0.52 points compared to the initial steady state.

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

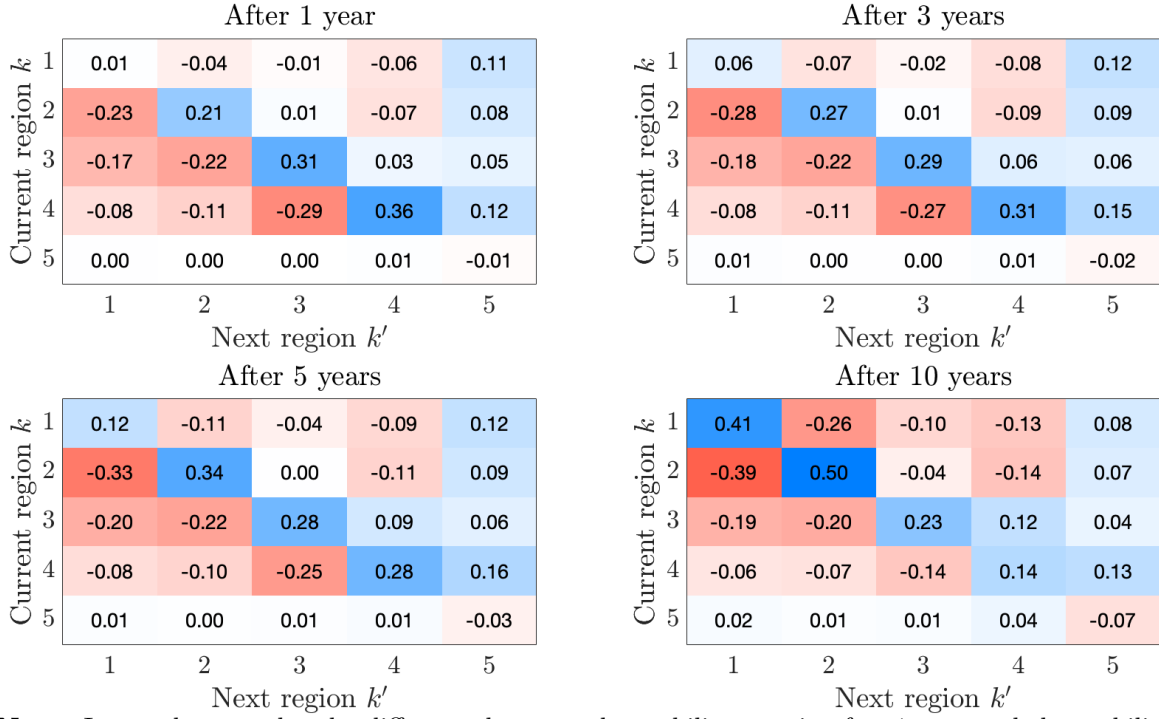
Figure 16: Mobility changes,  $\tau^h$  only



**Note:** In panel *a*, we plot the difference between the mobility matrix after 1 year and the mobility matrix of the initial steady state.

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

Figure 17: Mobility changes,  $\tau^f$  only



**Note:** In panel *a*, we plot the difference between the mobility matrix after 1 year and the mobility matrix of the initial steady state.

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

## E Additional results – Section 5

### E.1 $\tau^h$ vs $\tau^f$

In Table 12, we show the optimal values of  $\tau^h$  and  $\tau^f$  required to reduce emissions by 10%.<sup>21</sup> In the benchmark complete model 1, taxing households is costly in terms of welfare and inefficient at reducing emissions due to the incompressible energy consumption  $\bar{e}$ . Therefore, the optimal tax is significantly higher for firms than for households. If we remove the geographic dimension from our model by setting  $\bar{e}_k$ ,  $\gamma_k$ ,  $\omega_k$ , and  $z_k$  to their average values across all regions, the optimal  $\tau^h$  increases while  $\tau^f$  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  $\tau^h$ .

Table 12: Optimal taxes to reduce emissions by 10%

| Model | Description            | $\tau_h$ | $\tau_f$ | 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.

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<sup>21</sup>For a comparison, when  $\tau_h = \tau_f$  we get  $\tau = 0.155$ . When adjusting only one tax we get:  $\tau_h = 0.587$  and  $\tau_f = 0.446$ .

Table 13: Average welfare by location and income

|     | Scenario           | Rural | Small | Medium | Large | Paris | All   |
|-----|--------------------|-------|-------|--------|-------|-------|-------|
| (1) | Benchmark model: G | -1.11 | -1.10 | -1.03  | -1.02 | -0.94 | -1.05 |
| (2) | Uniform transfers  | 0.58  | 0.59  | 0.57   | 0.64  | 0.61  | 0.59  |
| (3) | Income rule        | 2.52  | 2.23  | 1.19   | 1.14  | 1.10  | 1.77  |
| (4) | Geo X Income       | 2.05  | 1.90  | 2.04   | 2.09  | 1.46  | 1.90  |
|     |                    | Q1    | Q2    | Q3     | Q4    | Q5    | All   |
| (1) | Benchmark model: G | -1.19 | -1.20 | -1.09  | -0.98 | -0.80 | -1.05 |
| (2) | Uniform transfers  | 1.40  | 0.83  | 0.47   | 0.22  | 0.08  | 0.59  |
| (3) | Income rule        | 6.32  | 2.06  | 0.44   | -0.02 | 0.06  | 1.77  |
| (4) | Geo X Income       | 6.67  | 2.25  | 0.51   | 0.03  | 0.09  | 1.90  |

**Notes:** Welfare is computed as wealth equivalent (in % of households’ disposable income) 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 18, 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  $\times$  Geography” scenario implies fewer migrations, as rich households in rural areas receive a transfer and therefore do not choose to migrate.

Figure 18: Migration dynamics

| a. Benchmark G |       |       |        |       |       |
|----------------|-------|-------|--------|-------|-------|
| Q1             | 0.09  | 0.04  | -0.14  | -0.05 | 0.03  |
| Q2             | 0.21  | 0.01  | -0.05  | -0.03 | -0.04 |
| Q3             | -0.16 | -0.02 | 0.00   | 0.00  | 0.12  |
| Q4             | -0.10 | -0.03 | 0.05   | 0.08  | -0.07 |
| Q5             | -0.20 | -0.04 | 0.08   | 0.03  | 0.17  |
|                | Rural | Small | Medium | Large | Paris |

| b. Uniform |       |       |        |       |       |
|------------|-------|-------|--------|-------|-------|
| Q1         | 0.20  | 0.14  | -0.22  | -0.16 | 0.04  |
| Q2         | 0.23  | 0.02  | -0.11  | -0.09 | 0.03  |
| Q3         | -0.16 | -0.03 | 0.08   | -0.01 | 0.03  |
| Q4         | -0.01 | -0.04 | -0.04  | 0.09  | -0.09 |
| Q5         | -0.32 | -0.04 | 0.13   | 0.08  | 0.21  |
|            | Rural | Small | Medium | Large | Paris |

| c. Income |       |       |        |       |       |
|-----------|-------|-------|--------|-------|-------|
| Q1        | 2.48  | 2.44  | -2.05  | -2.61 | -0.24 |
| Q2        | 0.68  | 0.47  | -0.80  | -0.05 | -0.22 |
| Q3        | -0.18 | -0.12 | 0.04   | 0.24  | 0.08  |
| Q4        | -0.55 | -0.63 | 0.54   | 0.56  | -0.10 |
| Q5        | -1.04 | -0.74 | 0.80   | 0.68  | 0.35  |
|           | Rural | Small | Medium | Large | Paris |

| d. Income x Geography |       |       |        |       |       |
|-----------------------|-------|-------|--------|-------|-------|
| Q1                    | 1.36  | 0.87  | -0.16  | -2.02 | -0.10 |
| Q2                    | -0.14 | -0.55 | -0.03  | 1.14  | -0.27 |
| Q3                    | -0.21 | -0.06 | 0.03   | 0.13  | 0.09  |
| Q4                    | -0.19 | -0.15 | 0.11   | 0.24  | -0.11 |
| Q5                    | -0.39 | 0.06  | -0.11  | 0.13  | 0.34  |
|                       | Rural | Small | Medium | Large | Paris |

**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 that are in rural areas and in the 1st quintile increases by 0.09 point 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

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

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                    | 2.15  | 1.98  | 1.27   | 1.30  | 1.20  | 1.66 |
| (2) | Income $\times$ Geography | 2.09  | 1.90  | 1.89   | 2.06  | 1.39  | 1.88 |
|     |                           | Q1    | Q2    | Q3     | Q4    | Q5    | All  |
| (1) | Income                    | 5.57  | 2.03  | 0.57   | 0.08  | 0.08  | 1.66 |
| (2) | Income $\times$ Geography | 6.51  | 2.23  | 0.52   | 0.04  | 0.09  | 1.88 |

**Notes:** Welfare is computed as wealth equivalent (in % of households' disposable income) 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):

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

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  $\xi$ . The parameter  $\xi$  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 19 compares our optimal inverse-rule formula with the transfer rule 7. The rule 19 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  $\xi_k$ <sup>22</sup> enhances aggregate welfare by +8.3%.

<sup>22</sup>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 19: Inverse formula vs. formula 7

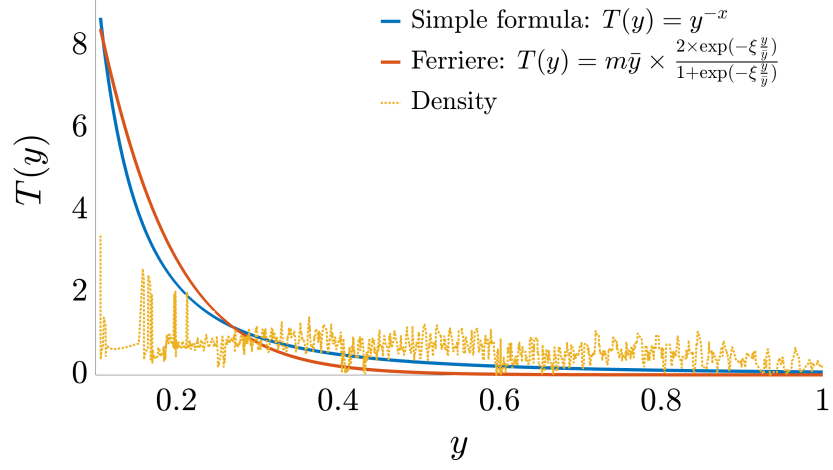


Table 16: Average welfare by location and income, alternative transfer rule

|     | Scenario                  | Rural | Small | Medium | Large | Paris | All  |
|-----|---------------------------|-------|-------|--------|-------|-------|------|
| (1) | Income                    | 2.46  | 2.31  | 1.54   | 1.51  | 1.39  | 1.93 |
| (2) | Income $\times$ Geography | 2.22  | 2.06  | 2.19   | 2.34  | 1.58  | 2.07 |
|     |                           | Q1    | Q2    | Q3     | Q4    | Q5    | All  |
| (2) | Income                    | 6.99  | 2.33  | 0.43   | -0.08 | 0.05  | 1.93 |
| (2) | Income $\times$ Geography | 7.51  | 2.45  | 0.42   | -0.07 | 0.08  | 2.07 |

**Notes:** Welfare is computed as wealth equivalent (in % of households' disposable income) 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 18.1% at the first line means that Rural households suffer a welfare loss 18.1% 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 | -1.11 | -1.10 | -1.03  | -1.01 | -0.94 | -1.05 | 18.1        |
| (2) | $\sigma = 0.4$     | -0.56 | -0.57 | -0.54  | -0.52 | -0.52 | -0.54 | 7.7         |
| (3) | $\epsilon_h = 1.3$ | -1.33 | -1.33 | -1.22  | -1.21 | -1.12 | -1.26 | 18.8        |
| (4) | $\sigma_y = 0.2$   | -1.01 | -1.01 | -0.94  | -0.93 | -0.86 | -0.96 | 17.5        |
| (5) | $\epsilon_y = 1.3$ | -1.26 | -1.25 | -1.15  | -1.14 | -1.06 | -1.19 | 18.9        |
| (6) | $\delta_H = 0.3$   | -1.12 | -1.12 | -1.03  | -1.02 | -0.93 | -1.06 | 20.4        |
|     |                    | Q1    | Q2    | Q3     | Q4    | Q5    | All   | Q1/Q5       |
| (1) | Benchmark model: G | -1.19 | -1.20 | -1.09  | -0.97 | -0.80 | -1.05 | 48.8        |
| (2) | $\sigma = 0.4$     | -0.58 | -0.61 | -0.56  | -0.52 | -0.47 | -0.54 | 23.4        |
| (3) | $\epsilon_h = 1.3$ | -1.40 | -1.44 | -1.31  | -1.18 | -0.96 | -1.26 | 45.8        |
| (4) | $\sigma_y = 0.2$   | -1.08 | -1.09 | -1.00  | -0.89 | -0.73 | -0.96 | 47.9        |
| (5) | $\epsilon_y = 1.3$ | -1.33 | -1.35 | -1.23  | -1.10 | -0.91 | -1.19 | 46.2        |
| (6) | $\delta_H = 0.3$   | -1.21 | -1.21 | -1.10  | -0.98 | -0.80 | -1.06 | 51.2        |

**Notes:** Welfare is computed as wealth equivalent (in % of households’ disposable income) 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  $\sigma$  substantially reduces welfare losses across all groups. For example, rural welfare losses decline to  $-0.56\%$  and the Q1 group’s losses drop to  $-0.58\%$ . 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 18.1% in the benchmark to 7.7%, and the Q1-to-Q5 gap drops from 48.8% to 23.4%.

*Elasticity of substitution between fossil fuels and electricity for households ( $\epsilon_h = 1.3$ ).* Reducing  $\epsilon_h$  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  $-1.33\%$  and Q1 losses increase  $-1.40\%$ . The rural-to-Paris welfare gap widens slightly to 18.8%, while the Q1-to-Q5 gap narrows modestly to 45.8%.

*Elasticity of substitution between capital-labor and energy for firms ( $\sigma_y = 0.2$ ).* With a higher  $\sigma_y$ , welfare costs are smaller for rural ( $-1.01$ ) and poor ( $-0.86$ ) households. The rural-to-Paris welfare gap decreases slightly to 17.5%, and the Q1-to-Q5 gap narrows to 47.9%. 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  $\epsilon_y$  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. The rural-to-Paris welfare gap widens slightly to 18.9% while the Q1-to-Q5 gap narrows modestly to 46.2%.

*Elasticity of housing supply ( $\delta_H = 0.3$ ).* Increasing  $\delta_H$  does not change aggregate losses ( $-1.05$  against  $-1.06$ ) but it amplifies distributive effects. The rural-to-Paris welfare gap increases significantly to 20.4%, while the Q1-to-Q5 gap widens to 51.2%. 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  $\tau$  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 | -1.11 | -1.10 | -1.03  | -1.01 | -0.94 | 18.1        |
| (2) | Partial equilibrium | -5.60 | -5.31 | -4.40  | -4.39 | -4.44 | 27.5        |
|     |                     | Q1    | Q2    | Q3     | Q4    | Q5    | Q1/Q5       |
| (1) | General equilibrium | -1.19 | -1.20 | -1.09  | -0.97 | -0.80 | 48.8        |
| (2) | Partial equilibrium | -5.02 | -5.27 | -5.41  | -4.78 | -4.07 | 23.3        |

**Notes:** Welfare is computed as wealth equivalent, in % of households’ disposable income. Last column: inequality ratio, defined as the percentage change between the first and the fifth column.

The welfare cost is significantly higher in partial equilibrium because households must fully bear the tax burden through changes in expenditures, without adjustments in wages, rents, or interest rates. While  $\tau^h$  allows households to substitute towards  $c$  and  $N$ , and  $\tau^f$  enables firms to substitute toward capital and labor, this unique  $\tau$  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.  $\tau^h$  is regressive because it disproportionately affects households with high fossil fuel consumption, and  $\tau^f$  is regressive through its negative impact on wages. In partial equilibrium, our  $\tau$  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 | -1.11 | -1.10 | -1.03  | -1.01 | -0.94 | -1.05 | 18.1        |
| (2) | $\delta_F = 0.1$   | -1.07 | -1.06 | -0.98  | -0.97 | -0.89 | -1.01 | 19.3        |
| (3) | $\delta_F = 0.5$   | -0.91 | -0.91 | -0.84  | -0.84 | -0.77 | -0.86 | 19.2        |
|     |                    | Q1    | Q2    | Q3     | Q4    | Q5    | All   | Q1/Q5       |
| (1) | Benchmark model: G | -1.19 | -1.20 | -1.09  | -0.97 | -0.80 | -1.05 | 48.8        |
| (2) | $\delta_F = 0.1$   | -1.14 | -1.15 | -1.05  | -0.93 | -0.77 | -1.01 | 48.3        |
| (3) | $\delta_F = 0.5$   | -0.98 | -0.98 | -0.89  | -0.80 | -0.66 | -0.86 | 48.5        |

**Notes:** Welfare is computed as wealth equivalent, in % of households' disposable income. Last column: inequality ratio, defined as the percentage change between the first and the fifth column.

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