Global Warming and Labor Market Reallocation

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Abstract

Global warming is a phenomenon expected to have heterogeneous effects across geographic locations and economic sectors. To assess its welfare consequences and the reallocation of workers across different markets, I develop a dynamic economic model with the patterns of structural transformation and spatially distinct labor markets facing varying exposure to warming damages on productivity. I incorporate trade of goods and migration across regions and industries, to account for the ability of agents to adapt to this phenomenon, and non-homothetic preferences, to reproduce the reallocation of economic activity when income grows. To measure workers' mobility, I collect data from censuses and population surveys, and employ methodologies from the demographic literature to provide novel estimates of worldwide bilateral migration flows. To identify the non-linear effects of temperature on productivity, I exploit weather fluctuations in a long panel and find that agricultural productivity in the hottest countries declines by 6% when temperature rises 1°C. The model, quantified for 6 sectors and 287 countries and subnational units, suggests that workers in agriculture face welfare losses three times larger than the average worker and that employment in this sector increases. Although hot regions might reduce the production of agricultural goods and import them from less affected locations, sectoral specialization is mainly driven by the shift in consumption expenditure towards the subsistence goods, as warming reduces global income.

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1 Introduction

Agriculture has been the focus of much of the research on climate damages. Unfortunately, much less is known about the impact of climate in other industries. To the extent that economic sectors vary in the number of tasks performed outdoors relative to indoors, it is natural to expect different climate sensitivities.[1] Hence, countries with similar temperature levels, like Congo and Australia, might experience different warming damages, as the former is mainly agricultural and the latter mostly oriented to services. Furthermore, increases in temperature not only affect productivity according to the industrial composition, but also according to the geographic location: rises in temperature are expected to be damaging in already hot regions, but beneficial in cold regions. Given the heterogeneous impacts in productivities across spatial and sectoral dimensions, this paper evaluates the reallocation of workers across industries and, ultimately, the welfare losses originated by this phenomenon.

To the extent that productivity might decline more in some markets and decline less, or even improve, in others, the possibility of trading goods across regions is expected to attenuate warming damages, as production of the most impaired industries might shift towards more temperate locations, while tropical areas might specialize in other, less climate sensitive, sectors. Nonetheless, comparative advantage is not the only factor driving sectoral specialization. Since global warming is expected to reduce average productivity and thus household's income, consumption patterns would shift towards the subsistence goods. The patterns of structural transformation would augment the relative demand for agricultural goods, rising the employment in this sector. As discussed in Nath (2020), the ultimate effect on sectoral reallocation is a horserace between the production and consumption specialization.

The final effect of sectoral reallocation is a quantitative question that requires the development and estimation of a model that recognizes that the strength of the production and consumption specialization is mediated by the cost of moving goods and persons across markets. Hence, I develop a dynamic economic model with the patterns of structural transformation and spatially distinct labor markets facing varying exposure to warming damages on productivity. In this assessment model, workers value consumption across goods according to non-homothetic preferences, so that an increase in income reduces the consumption share of subsistence goods, namely, agricultural goods. The model incorporates non-homothetic preferences to reproduce the reallocation of economic activity across sectors when income grows. In addition, workers face a forward-looking dynamic decision, in terms of where to reside and work in the next period, so that the migration costs depend on both the market of origin and destination, and a market is defined as a region-sector pair. In each market, competitive firms produce intermediate varieties, using labor, land, energy, and materials from every sector. Trade in intermediate varieties is costly. The model explicitly recognizes the role of trade of goods and migration of workers, to account for the ability of agents to adapt to this phenomenon. Energy is produced from two sources: clean energy or fossil fuels. The use of the latter type of energy generates carbon dioxide emissions that accrue in the atmosphere, warming up the Earth, and rising local temperature. The modification of local climate conditions distort the evolution of productivity faced by firms in heterogeneous ways across regions and sectors.

To underscore the vast heterogeneity in temperature and industrial composition across geographic locations, I pursue a high level of resolution and take the model to the data by considering 6 economic sectors

[1] Seppanen et al. (2003) surveys lab experiments studying the relationship between temperature and labor productivity, by randomly assigned subjects to rooms of different temperatures and asked them to perform cognitive and physical tasks. There is a general detriment in work performance when temperatures exceeded a certain threshold.

and 287 regions.[2] Since most of the trade and migration flows occur within, rather than across national borders, I disaggregate the 6 largest countries, in a demographic and economic sense, into their subnational constituent units, namely, United States, Canada, Brazil, India, China and Russia.[3] The quantification of a multi-sector multi-region dynamic assessment model with the aforementioned mechanisms at such level of industrial and spatial resolution implies an intensive data collection process. To this end, I resort to a large array of international and domestic data on consumption, employment, value added, fossil fuels, and clean energy use, to construct these variables at the market-level. In addition, I employ international trade and national customs data to measure national and subnational sector-specific commercial flows.

Measuring the worldwide mobility patterns of workers across markets is challenging, due to the lack of reliable international migration flow data.[4] Due to this constraint, a branch of the demographic literature (Abel, 2013; Abel and Sander, 2014; Azose and Raftery, 2019) has inferred migration flows from changes in bilateral migrant stocks across periods. Migration stocks can be collected from countries' censuses or population surveys, as they only require information on the number persons by birthplace in each location at a particular point in time. Therefore, I resort to a large set of international and national sources of migration stocks, and extend the methodologies developed by this strand of the literature to compute bilateral migration flows across countries, subnational units and economic sectors, leading to a migration matrix with almost three million entries across markets of origin and destination.

To quantify the impact of temperature increases on productivity, I assemble a long panel of weather fluctuations and value added productivity, and exploit the temporal variation in a fixed effect econometric model to identify the non-linear effect of warming on productivity. Agriculture and construction stand out as the most climate sensitive sectors, so that an increase of local temperature of 1°C in the coldest countries of the world significantly rises productivity by 3%. But in the hottest countries, productivity declines by roughly 6%.[5] Finance and government and other services show minuscule and insignificant results. The heterogeneity of sectoral responses to temperature increases asks for a granular assessment of this phenomenon. The aforementioned results hold under an extensive set of robustness exercises.

The simulation of the model suggests a huge degree of heterogeneity in terms of welfare across locations. Workers in India are projected to suffer welfare losses 15 times larger than the global average. However, some regions are expected to be benefited, states in Far East Russia might experience welfare gains as large as 10%. The heterogeneity in temperature in the African Continent leads to smaller losses in the northern countries relative to the central regions, as their lower temperatures allows them to harness in the comparative advantage in producing agricultural goods to attenuate the warming damages. The heterogeneity in industrial composition implies higher welfare losses in the Northern States of India and the Southern Coastal Provinces of China, as they are mostly agrarian in comparison with the rest of the national territory. The spatial composition of welfare losses in the United States and Canada does not largely respond to the

[2] The economic sectors of interest are agriculture, industry, construction, trade and transportation, finance, and government and other services.

[3] To properly gauge the distribution of warming damages, it is not only important to analyze a larger number of regions and sectors, but also to model their local characteristics and underscore the interactions, in terms of goods and workers, among them (Caliendo et al., 2017).

[4] In many countries, such data is not collected, as reporting systems are expensive, and the ones that collect them have different definitions of what constitutes a migrant in terms of the length or purpose of stay, and might only consider the formal migration movements. Therefore, missing and non-comparable data preclude an accurate measurement of the global migration patterns.

[5] Relative to these sectors, trade and transportation display smaller but significant results. Relative to trade and transportation, industry exhibits smaller responses.

allocation of agriculture and construction, since these sectors represent a small share in the total economy. Instead, the trade and transportation sector mainly explains the differences across states.

The heterogeneity of productivity responses to higher temperature induce a reallocation of workers across economic sectors and geographic locations. On aggregate, warming rises the employment level in agriculture and reduces it in services. Although hot regions have the possibility to reduce the production of agricultural goods and import them from less affected locations, sectoral specialization is mainly driven by the shift in consumption expenditure towards the subsistence goods, as warming reduces global income. As a consequence, workers in the agriculture sector experience the largest welfare losses: three times higher than the average worker. Even though at the global scale, the higher subsistence food requirement dominates the comparative advantage effect, such balance varies over space. In poor and warm countries, undergoing the largest income declines, the increase of employment in agriculture is the highest. Therefore, when temperature rises the forces of structural transformation perversely allocate more workers into the most affected markets.

This paper contributes to several strands of the literature. First, this paper quantifies bilateral migration flows across markets at a global scale and embeds these estimates in a micro-founded model. A branch of the literature (Schutte et al., 2021; Missirian and Schlenker, 2017a,b) has empirically estimated the reaction of migration to changes in temperature. Their limited geographical scope precludes a global analysis of the migration patterns. Alternatively, some studies have constructed economic models of climate change integrating migration of households, but they lack a micro-founded motive (Benveniste et al., 2020), or assume extreme migration frictions (Desmet and Rossi-Hansberg, 2015; Conte et al., 2020), mainly free mobility across sectors. Second, this work advances on the estimation of warming damages on fundamental productivities, rather than on endogenous economic objects, like GDP or GDP per capita, (Burke et al., 2015; Dell et al., 2012), or on productivities for a subset of industries (Somanathan et al., 2021; Zhang et al., 2018; Schlenker and Roberts, 2009) or geographic locations (Colacito et al., 2019).

Finally, I exploit recent contributions on spatial dynamic economic models (Caliendo et al., 2019, 2021; Desmet et al., 2018; Kleinman et al., 2021) to accommodate the essential features of structural transformation (Comin et al., 2021; Tombe, 2015), and integrate an endogenous energy and climate component (Anthoff and Tol, 2014; Hope and Hope, 2013; Nordhaus, 2017). There is an incipient literature evaluating the economic consequences of global warming through the lens of these type of models. In a one-sector model, Cruz and Rossi-Hansberg (2021) evaluate the effect of increases of temperature on the aggregate dynamic behavior of the economy, by developing a model with endogenous population growth and local technological innovations. Desmet and Rossi-Hansberg (2015) and Conte et al. (2020) evaluate the reaction of the local growth rate of the agriculture and non-agriculture sectors when temperature rises, assuming labor is freely mobile across sectors and abstracting away from the changes in consumption specialization. Rudik et al. (2021) construct a forward-looking dynamic spatial model with warming damages on productivity growth rates and amenities, whose quantification mainly focuses on the United States, hampering a proper assessment of the migration frictions elsewhere in the world, and keeping fixed the consumption patterns over time. Nath (2020) pioneers the study of sectoral specialization, considering that both production and consumption patterns might respond to changes in temperature, in an economy with a coarser industrial and spatial resolution (three-sector country-level) and extreme mobility frictions (free industry switching but precluding spatial mobility).

This paper is organized as follows: Section 2 describes the economic model of global warming. Section 3 outlines the solution method. Section 4 discusses the quantification of the model. Section 5 explores the effects of warming on welfare and labor reallocation. Section 6 concludes.

2 The Model

I develop a spatial dynamic general equilibrium model. Time is discrete and the economy has J sectors and R regions. In each sector and region, there is a mass of workers who supply labor inelastically. Workers decide how much to consume of every good according to non-homothetic preferences. Additionally, they face a forward-looking dynamic decision of where to reside and work in the next period. In each region, there is an immobile landlord who rents the fixed factor to the firms and decides how much to consume of every good. In each market, there is a continuum of firms producing intermediate varieties, using labor, land, energy and materials from every sector. These intermediate varieties can be costly traded across regions. Final firms bundle varieties (from home and abroad) to produce final goods, which can be used as consumption by workers and landlords or as materials by firms in the production of intermediate varieties. Energy inputs can come from clean sources or fossil fuels. The use of the latter type of energy generates carbon dioxide emissions that accrue in the atmosphere, warming up the Earth and rising local temperature. The modification of local climate conditions distorts the evolution of productivity faced by firms in heterogeneous ways across regions and sectors.

2.1 Workers

In each sector j and region r, there is a mass of workers who supply one unit of labor inelastically at the market wage w_t^{jr}. Given the workers' income, they decide how to allocate consumption over local final goods from all sectors through a CES non-homothetic aggregator, as in Comin et al. (2021).[6] More precisely, workers minimize expenditure subject to a utility level, implicitly defined by the constraint (1),

$$
\begin{aligned}
w_t^{jr} = \min \quad & \sum_{\tilde{j}=1}^{J} p_t^{\tilde{j}r} c_t^{(jr)(\tilde{j})} \\
\text{st} \quad & \sum_{\tilde{j}=1}^{J} \left(\gamma^{\tilde{j}}\right)^{\frac{1}{\varsigma}} \left(c_t^{jr}\right)^{-\frac{\vartheta^{\tilde{j}}}{\varsigma}} \left(c_t^{(jr)(\tilde{j})}\right)^{\frac{\varsigma-1}{\varsigma}} = 1,
\end{aligned} \tag{1}
$$

where $c_t^{(jr)(\tilde{j})}$ denotes the consumption level of good $\tilde{j}$ by a household working in sector j and residing in region r, c_t^{jr} represents the utility level, or real consumption, of a worker in market jr, where a market is defined as the pair of a sector and a region, and $p_t^{\tilde{j}r}$ is the price of goods purchased from sector $\tilde{j}$ for final consumption in region r. The solution of the expenditure minimization problem defines the consumption share of good $\tilde{j}$ by a worker in market jr, $s_t^{(jr)(\tilde{j})}$, relative to her total consumption spending,

$$
s_t^{(jr)(\tilde{j})} = \frac{p_t^{\tilde{j}r} c_t^{(jr)(\tilde{j})}}{w_t^{jr}} = \gamma^{\tilde{j}} \left(\frac{w_t^{jr}}{p_t^{\tilde{j}r}}\right)^{\varsigma-1} \left(c_t^{jr}\right)^{\vartheta^{\tilde{j}}}. \tag{2}
$$

The parameter $\gamma^{\tilde{j}}$ is the fixed sectoral taste of good $\tilde{j}$, ς represents the elasticity of substitution between

[6] I choose this specification, rather than Stone-Geary or other types of non-homothetic preferences (Boppart, 2014) because they can accommodate an arbitrary number of goods, provide a better fit to the patterns of structural transformation and given their log-linear structure they are particularly tractable with the hat-algebra method.

goods, and $\vartheta^{\tilde{\jmath}}$ governs the sector $\tilde{\jmath}$-specific income elasticity.[7] When $\vartheta^{\tilde{\jmath}}$ varies across goods, an increase in income induces a more than proportional rise in consumption of the goods with income elasticity larger than one. This preferences collapses to the standard CES aggregator when $\vartheta^{\tilde{\jmath}} = \varsigma - 1$ and Cobb Douglas when, in addition, $\varsigma = 1$.

After consuming and working, each household observes the conditions in all markets and decides where to reside and work in the next period. Workers are forward-looking, have perfect foresight and discount the future at a rate β. The dynamic migration decision follows Caliendo et al. (2019) and Artuç et al. (2010). Moving from market jr to $j'r'$ entails a publicly known bilateral cost, $\chi_t^{(jr)(j'r')}$, measured in terms of utility and an idiosyncratic benefit, $\epsilon_t^{j'r'}$, which is independently and identically distributed across workers, markets and periods, has mean zero and is observed by the worker before the migration decision.

Consequently, the worker's problem can be posed as the following dynamic discrete choice model,

$$v_t^{jr} = \log(c_t^{jr}) + \log(B_t^{jr}) + \max_{j'r'} \left(-\chi_t^{(jr)(j'r')} + \epsilon_t^{j'r'} + \beta \mathbb{E} v_{t+1}^{j'r'} \right). \tag{3}$$

The contemporaneous value of residing and working in market jr, v_t^{jr}, depends on the level of utility, c_t^{jr}, and amenities, B_t^{jr},[8] as well as the continuation value of the option value of moving to a new market $j'r'$, comprising the bilateral moving cost, the idiosyncratic benefit and the discounted expected continuation value, $\beta \mathbb{E} v_{t+1}^{j'r'}$, where the expectation is taken over future preference shocks.

To allow for a parsimonious aggregation of individual decisions, I assume that $\epsilon_t^{j'r'}$ follows a Gumbel distribution with location parameter $\bar{\gamma}$ and scale parameter $\bar{\gamma}\nu$, where $\bar{\gamma}$ is the Euler-Mascheroni constant and ν governs the dispersion of the idiosyncratic shock. Under the previous assumption, equation (3) can be rewritten as:

$$V_t^{jr} := \mathbb{E} v_t^{jr} = \log(c_t^{jr}) + \log(B_t^{jr}) + \nu \log \left(\sum_{j'=1}^{J} \sum_{r'=1}^{R} \exp \left(\beta V_{t+1}^{j'r'} - \chi_t^{(jr)(j'r')} \right)^{1/\nu} \right). \tag{4}$$

The individual mobility decisions of workers determine the evolution of labor across markets,

$$L_{t+1}^{j'r'} = \sum_{j=1}^{J} \sum_{r=1}^{R} L_t^{jr} \mu_t^{(jr)(j'r')}, \tag{5}$$

where the variable $\mu_t^{(jr)(j'r')}$ denotes the share of workers moving from market jr to $j'r'$. Due to the structure of the model, this variable adopts a gravity structure, so that markets with higher lifetime utility attract more migrants. The parameter $1/\nu$ can be interpreted as the migration elasticity, that is, the sensitivity of migration shares to changes in lifetime utility, namely,

$$\mu_t^{(jr)(j'r')} = \frac{\exp \left(\beta V_{t+1}^{j'r'} - \chi_t^{(jr)(j'r')} \right)^{1/\nu}}{\sum_{\tilde{\jmath}=1}^{J} \sum_{\tilde{r}=1}^{R} \exp \left(\beta V_{t+1}^{\tilde{\jmath}\tilde{r}} - \chi_t^{(jr)(\tilde{\jmath}\tilde{r})} \right)^{1/\nu}}. \tag{6}$$

[7]The elasticity of substitution across goods, $\partial \log(c_t^{(jr)(\tilde{\jmath})}/c_t^{(jr)(\hat{\jmath})})/\partial \log(p_t^{\tilde{\jmath}r}/p_t^{\hat{\jmath}r}) = \varsigma$, and the elasticity of relative demand for two different goods with respect to utility, $\partial \log(c_t^{(jr)(\tilde{\jmath})}/c_t^{(jr)(\hat{\jmath})})/\partial \log(c_t^{jr}) = \vartheta^{\tilde{\jmath}} - \vartheta^{\hat{\jmath}}$, do not depend on the income level.

[8]In this paper, I assume that the only mechanism through which warming affects the workings of the economy is by distorting productivities. Cruz and Rossi-Hansberg (2021) study the effect of temperature increases on amenities in a one-sector model.

2.2 Landlords

In each region r, there is a unit mass of landlords who own the local factor, H^r, and rent it to the local firms at the market price q_t^r. Landlords use their income, $q_t^r H^r$, to purchase local goods that are valued according to the same non-homothetic CES preferences as workers. Hence, the consumption share of good $\tilde{\jmath}$ by a landlord in region r is given by,

$$s_t^{(\tilde{\jmath}r)} = \gamma^{\tilde{\jmath}} \left(\frac{q_t^r H^r}{p_t^{\tilde{\jmath}r}} \right)^{\varsigma - 1} (c_t^r)^{\vartheta^{\tilde{\jmath}}}, \tag{7}$$

where c_t^r represents the utility level of the immobile landlord located in region r. Since landlords cannot relocate to other regions, they face no dynamic decision.

2.3 Intermediate sector

The production component of the model follows the multi-sector model of Caliendo and Parro (2014) and the spatial model of Caliendo et al. (2017). In each region r and sector j, there is a continuum of intermediate firms, each producing a differentiated variety, indexed by its idiosyncratic productivity z. Average value added productivity at the market level is represented as the product of an exogenous component, A_t^{jr}, and an endogenous component, $\Omega^j(T_t^r)$, varying according to the level of local temperature.

The production of intermediate varieties requires labor $l_t^{jr}(z)$, land $h_t^{jr}(z)$, energy $e_t^{jr}(z)$ and materials $m_t^{(\tilde{\jmath}r)(jr)}(z)$ from all sectors $\tilde{\jmath} \in \{1, \cdots, J\}$, aggregated through a Cobb Douglas composite,

$$y_t^{jr}(z) = z \left(A_t^{jr} \Omega^j \left(T_t^r \right) \right)^{1-\omega^{jr}} \left(\left(l_t^{jr}(z)^{\alpha^L} h_t^{jr}(z)^{\alpha^H} e_t^{jr}(z)^{\alpha^E} \right)^{1-\omega^{jr}} \left(\prod_{\tilde{\jmath}=1}^{J} m_t^{(\tilde{\jmath}r)(jr)}(z)^{\omega^{(\tilde{\jmath}r)(jr)}} \right)^{\omega^{jr}} - p_t^{e,jr} e_t^{jr}(z) \right). \tag{8}$$

The parameters $\alpha^L, \alpha^H, \alpha^E$ denote the shares of labor, structures and energy in value added, respectively, which are identical across markets and add up to one. The market-specific parameter ω^{jr} represents the share of value added in gross production in market jr and $\omega^{(\tilde{\jmath}r)(jr)}$ is the share of of materials from sector $\tilde{\jmath}$ in the production of sector j and region r. Since the production function displays Constant Returns to Scale, $\sum_{\tilde{\jmath}=1}^{J} \omega^{(\tilde{\jmath}r)(jr)} = 1$. The variable $y_t^{jr}(z)$ denotes the production of goods after subtracting the cost of generating energy, $p_t^{e,jr} e_t^{jr}(z)$, where $p_t^{e,jr}$ represents the market-specific price of energy and $e_t^{jr}(z)$ is expressed in terms of the intermediate varieties of the same market.[9] This specification follows Nordhaus and Boyer (2002).

Like in Cruz and Rossi-Hansberg (2021), the energy input is a CES composite between fossil fuels, $e_t^{f,jr}(z)$, and clean sources, $e_t^{c,jr}(z)$,

$$e_t^{jr}(z) = \left(\eta^{jr} e_t^{f,jr}(z)^{\frac{1-\zeta}{\zeta}} + (1 - \eta^{jr}) e_t^{c,jr}(z)^{\frac{1-\zeta}{\zeta}} \right)^{\frac{\zeta}{1-\zeta}}. \tag{9}$$

The parameter ζ represents the elasticity of substitution between energy inputs and η^{jr} controls the market-

[9] Alternatively, energy could be defined in terms of labor. However, such specification would require to explicitly quantify the number of workers in the energy generation sector, which is a subset of manufacturing, mining and utilities.

specific intensity of fossil fuels relative to clean sources.[10] Firms can generate one unit of fossil fuels and clean energy by paying the costs $p_t^{f,jr}$ and $p_t^{c,jr}$, respectively. These prices are taken as given by the firms and are given by,

$$p_t^{f,jr} = \frac{h(\Upsilon_t)}{A_t^{f,jr}}, \qquad p_t^{c,jr} = \frac{1}{A_t^{c,jr}}. \tag{10}$$

In this formulation, $A_t^{f,jr}$ and $A_t^{c,jr}$ are the exogenous productivity levels of energy generation. In addition, the price of fossil fuels includes a component representing the increasing and convex cost of extracting fossil fuels, $h(\cdot)$, in terms of the global cumulative use of this resource, Υ_t. According to this specification, extracting fossil fuels is cheap when they are abundant, but the cost rises as the resource is depleted. The evolution of cumulative extraction follows

$$\Upsilon_t = E_t^f + \Upsilon_{t-1}, \quad \text{with} \quad E_t^f = \sum_{j=1}^{J} \sum_{r=1}^{R} \int e_t^{f,jr}(z) dF(z). \tag{11}$$

Assuming a competitive market for intermediate goods and that intermediate firms do not internalize climate damages, the price, $p_t^{jr}(z)$, of a given variety equals its unit cost, as displayed in equation (12). The variable $\varkappa_t^{jr}$ denotes the cost of the input bundle required to produce one unit of intermediate variety in market jr, p_t^{ir} is the price of final good i used as materials in region r, and $\alpha^W = 1 - \alpha^E(1-\omega^{jr})$ and R^{jr} are time invariant constants,[11]

$$\begin{aligned} p_t^{jr}(z) &= \frac{\varkappa_t^{jr}}{z\left(A_t^{jr}\Omega^j(T_t^r)\right)^{1-\omega^{jr}}}, \\ \varkappa_t^{jr} &:= R^{jr}\left(\left(w_t^{jr}\right)^{\alpha^L}\left(q_t^r\right)^{\alpha^H}\left(p_t^{e,jr}\right)^{\alpha^E}\right)^{(1-\omega^{jr})/\alpha^W}\left(\prod_{\tilde{j}=1}^{J}\left(p_t^{\tilde{j}r}\right)^{\omega^{(\tilde{j}r)(jr)}}\right)^{\omega^{jr}/\alpha^W}. \end{aligned} \tag{12}$$

2.4 Final sector

In each sector j and region r, there is a firm that bundles a continuum of varieties (from home and abroad) to produce final goods x_t^{jr}, according to the following technology,

$$x_t^{jr} = \left(\int x_t^{jr}(z)^{\frac{\xi-1}{\xi}} dF(z)\right)^{\frac{\xi}{\xi-1}}, \tag{13}$$

where $x_t^{jr}(z)$ is the quantity of intermediate variety z demanded by the production of good j in region r and ξ governs the elasticity of substitution among varieties.[12] Since each variety z is purchased from the

[10] This energy modeling assumes that all the different energy uses, like transportation, are embedded in the production process. Energy use of transportation comprises less than 2% of the global total electricity use in the year 2015, according to IEA (2019).

[11] More precisely, $R^{jr} = \left(\left(1-\omega^{jr}\right)\left(\alpha^L\right)^{\alpha^L}\left(\alpha^H\right)^{\alpha^H}\left(\alpha^E\right)^{\alpha^E}\right)^{-(1-\omega^{jr})/\alpha^W}\left(\omega^{(jr)}\prod_{\tilde{j}=1}^{J}\left(\omega^{(\tilde{j}r)(jr)}\right)^{\omega^{(\tilde{j}r)(jr)}}\right)^{-\omega^{(jr)}/\alpha^W}$.

[12] To account for damages on productivity due to global warming, these impacts must be accounted for in either the intermediate or the final sector to avoid double counting. The model is much more parsimonious when considering the former specification.

region with the lowest cost (inclusive of freight), the price paid for variety z, $\tilde{p}_t^{jr}(z)$, can be defined as,

$$\tilde{p}_t^{jr}(z) = \min_{\tilde{r}} \left\{ p_t^{j\tilde{r}}(z) \kappa_t^{(j\tilde{r})(jr)} \right\} \tag{14}$$

Moving intermediate good j from region $\tilde{r}$ to r entails an iceberg bilateral cost $\kappa_t^{(j\tilde{r})(jr)} \geq 1$. To allow for a parsimonious aggregation of individual decisions, I assume that z follows a Fréchet distribution with shape parameter θ and scale parameter 1. The parameter θ governs the dispersion of productivity, such that a smaller value implies a higher dispersion of productivity, a notion of comparative advantage. Given the properties of the Fréchet distribution, with marginal distribution $F(z) = \exp(-z^{-\theta})$, the price of the sectoral aggregate good j in region r at period t is given by equation (15),

$$p_t^{jr} = \left(\int \tilde{p}_t^{jr}(z)^{1-\xi} dF(z) \right)^{\frac{1}{1-\xi}} = \hat{\Gamma} \left(\sum_{\tilde{r}=1}^{R} \left(\varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \right)^{-\theta} \left(A_t^{j\tilde{r}} \Omega^j (T_t^{\tilde{r}}) \right)^{\theta(1-\omega^{j\tilde{r}})} \right)^{-1/\theta}, \tag{15}$$

where $\hat{\Gamma}$ is a constant.[13] Since there are a continuum of varieties, the trade share $\pi_t^{(j\tilde{r})(jr)}$ can be interpreted as the fraction of varieties of good j that are purchased by region r from region $\tilde{r}$. Due to the structure of the model, this variable adopts a gravity structure, so that markets with lower costs attract more transactions, namely,

$$\pi_t^{(j\tilde{r})(jr)} = \frac{\left(\varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \right)^{-\theta} \left(A_t^{j\tilde{r}} \Omega^j (T_t^{\tilde{r}}) \right)^{\theta(1-\omega^{j\tilde{r}})}}{\sum_{\hat{r}=1}^{R} \left(\varkappa_t^{j\hat{r}} \kappa_t^{(j\hat{r})(jr)} \right)^{-\theta} \left(A_t^{j\hat{r}} \Omega^j (T_t^{\hat{r}}) \right)^{\theta(1-\omega^{j\hat{r}})}}. \tag{16}$$

2.5 Market Clearing

By employing the optimality conditions of the intermediate firms, labor market clearing in sector j and region r and land market clearing in region r are given by,

$$w_t^{jr} L_t^{jr} = \int w_t^{jr} l_t^{jr}(z) dF(z) = (\alpha^L/\alpha^W)(1-\omega^{jr}) Y_t^{jr}, \tag{17}$$

$$q_t^r H^r = \sum_{j=1}^{J} \int q_t^r h_t^{jr}(z) dF(z) = \sum_{j=1}^{J} (\alpha^H/\alpha^W)(1-\omega^{jr}) Y_t^{jr}, \tag{18}$$

where $Y_t^{jr} = \int p_t^{jr}(z) y_t^{jr}(z) dF(z)$ represents the total production of intermediate varieties in market jr. The market clearing for intermediate varieties implies that the total production in market jr must be equal to the global purchases of good j, including the iceberg trade costs,

$$Y_t^{jr} = \sum_{\tilde{r}=1}^{R} \pi_t^{(jr)(j\tilde{r})} X_t^{j\tilde{r}}. \tag{19}$$

The variable $X_t^{j\tilde{r}} = p_t^{j\tilde{r}} x_t^{j\tilde{r}}$ is the total expenditure on sector j goods in region $\tilde{r}$. Spending can be devoted to: final consumption by workers in each economic sector, final consumption by landlords, and

[13] More precisely, $\hat{\Gamma} = \Gamma(1 + (1-\xi)/\theta)^{1/(1-\xi)}$. Where $\Gamma(\cdot)$ is the Gamma function and the parameters must satisfy $1 + \theta > \xi$ for the Gamma function to be well defined.

use as materials across different industries.[14] Hence,

$$X_t^{jr} = \sum_{\tilde{j}=1}^{J} s_t^{(\tilde{j}r)(j)} w_t^{\tilde{j}r} L_t^{\tilde{j}r} + s_t^{jr} \sum_{\tilde{j}=1}^{J} (\alpha^H/\alpha^L) w_t^{\tilde{j}r} L_t^{\tilde{j}r} + \sum_{\tilde{j}=1}^{J} (\omega^{(jr)(\tilde{j}r)} \omega^{\tilde{j}r}/\alpha^W) \sum_{\tilde{r}=1}^{R} \pi_t^{(\tilde{j}r)(\tilde{j}\tilde{r})} X_t^{\tilde{j}\tilde{r}}. \tag{20}$$

2.6 Carbon Circulation and Climate

Global carbon dioxide emissions, E_t, are defined as the sum of two components: the endogenous usage of fossil fuels in the production process, E_t^f, and the exogenous carbon dioxide from forestry and land use change, E_t^x.[15] Carbon emissions enter into a circulation system between different carbon reservoirs. I follow Golosov et al. (2014) and Hassler et al. (2016) and specify a reduced-form depreciation model of the atmospheric carbon concentration,[16]

$$S_{t+1} = S_{\text{pre-ind}} + \sum_{\ell=0}^{t+1} (1-\delta_\ell) E_{t-\ell},$$

where S_{t+1} denotes the stock of carbon in the atmosphere at the beginning of period $t+1$, $S_{\text{pre-ind}}$ represents the accumulation of carbon in the pre-industrial era (middle of eighteenth century) and $(1-\delta_\ell)$ denotes the amount of carbon dioxide that is left in the atmosphere ℓ periods in the future and is parametrized as,[17]

$$(1-\delta_\ell) = \psi_L + (1-\psi_L)\psi_0(1-\psi)^\ell.$$

This carbon circulation process is equivalent to a recursive vector representation , where carbon stock is posed as the sum of two components: a persistent, $S_{1,t+1}$, and a slowly depreciating, $S_{2,t+1}$, process.

$$S_{t+1} = S_{1,t+1} + S_{2,t+1}, \tag{21}$$

$$S_{1,t+1} = S_{1,t} + \psi_L E_t, \tag{22}$$

$$S_{2,t+1} = (1-\psi) S_{2,t} + \psi_0 (1-\psi_L) E_t. \tag{23}$$

The accumulation of carbon in the atmosphere generates a positive net inflow of energy to the planet. The relationship between carbon stock and the anthropogenic change in the Earth's energy budget, or forcing F_{t+1}, is well approximated by a logarithmic function (Arrhenius' Greenhouse Law, Arrhenius (1896)),

$$F_{t+1} = F_{\text{pre-ind}} + \varphi \log_2 \left(\frac{S_{t+1}}{S_{\text{pre-ind}}} \right). \tag{24}$$

The variable $F_{\text{pre-ind}}$ denotes the forcing in the pre-industrial era and φ can be interpreted as the forcing

[14] Note that from the optimality conditions of the intermediate firms, the landlord's income in region r can be rewritten as $q_t^r H^r = \sum_{\tilde{j}=1}^{J} (\alpha^H/\alpha^L) w_t^{\tilde{j}r} L_t^{\tilde{j}r}$ and the cost of materials from sector j by firms in sector $\tilde{j}$ and region r can be expressed as $\int p_t^{jr} m_t^{(jr)(\tilde{j}r)}(z) dF(z) = (\omega^{(jr)(\tilde{j}r)} \omega^{\tilde{j}r}/\alpha^W) Y_t^{\tilde{j}r}$.

[15] This stand is based on the fact that CO_2 from fossil fuel combustion represented more than 90% of the total emissions of carbon dioxide in the year 2011 (IPCC, 2014).

[16] IPCC (2021) proposes a depreciation model of carbon circulation and temperature with a larger number of climate stocks. A more accurate climate description comes at the cost of a larger state space.

[17] The parameter ψ_L denotes the share of carbon emitted into the atmosphere, $(1-\psi_0)$ is the share of emissions exiting the atmosphere immediately and ψ represents the depreciation rate of CO_2 every period.

increase when the carbon stock doubles relative to its pre-industrial level. The positive change in the Earth's energy budget warms up the atmospheric layer.[18] Global temperature at the beginning of period $t+1$, T_{t+1}, is proportional to forcing, namely,

$$T_{t+1} = T_{\text{pre-ind}} + \frac{\lambda}{\varphi}\left(F_{t+1} + F_{t+1}^{x} - F_{\text{pre-ind}}\right). \tag{25}$$

where F_{t+1}^{x} denotes the exogenous forcing from greenhouse gases (GHG) other than carbon dioxide, and λ is the climate sensitivity, which admits a similar interpretation to φ. Since the energy flow to the Earth is unevenly spread over space, local temperature might evolve differently, depending on the geographic position and natural attributes of each region.

I derive the evolution of local temperature at region r, T_{t+1}^{r}, as a function of its global value, T_{t+1}. More precisely, I employ a linear statistical downscaling to derive the relation between aggregate and disaggregated variables,[19]

$$\left(T_{t+1}^{r} - T_{t}^{r}\right) = g^{r}\left(T_{t+1} - T_{t}\right), \tag{26}$$

where the coefficient g^{r} quantifies the increase in local temperature in region r when global temperature rises one degree Celsius.

2.7 Competitive Equilibrium

The endogenous state variables of the economy are the stock of carbon dioxide of both layers, $S_{1,t}, S_{2,t}$, the cumulative extraction of carbon from the ground, Υ_t, and the distribution of population across markets, $L_t = \{L_t^{jr}\}_{j=1,r=1}^{J,R}$. The exogenous state variables of the economy are the fundamental productivities, amenities, mobility and transport costs, $\Theta_t = (A_t, A_t^{f}, A_t^{c}, B_t, \chi_t, \kappa_t)$ with $(A_t^{jr}, A_t^{f,jr}, A_t^{c,jr}, B_t^{jr}) = \{A_t^{jr}, A_t^{f,jr}, A_t^{c,jr}, B_t^{jr}\}_{j=1,r=1}^{J,R}$, $\chi_t = \{\chi_t^{(jr)(j'r')}\}_{j=1,j'=1,r=1,r'=1}^{J,J,R,R}$, $\kappa_t = \{\kappa_t^{(jr)(j\tilde{r})}\}_{j=1,\tilde{r}=1,r'=1}^{J,R,R}$, and the exogenous flow variables are the non-fossil fuels CO_2 emissions and the non-CO_2 GHG forcing, $\Phi_t = (E_t^{x}, F_t^{x})$. I define a competitive equilibrium following the terminology of Caliendo et al. (2019) and Caliendo et al. (2021).

Definition 1. *Given $(L_t, S_{1,t}, S_{2,t}, \Upsilon_t, \Theta_t, \Phi_t)$, a temporary competitive equilibrium is the set of variables $Z_t = (q_t, w_t, p_t^{e}, \varkappa_t, p_t, c_t, X_t, \pi_t, s_t)$, where $q_t = \{q_t^{r}\}_{r=1}^{R}$, $(w_t, p_t^{e}, \varkappa_t, p_t, c_t, X_t) = \{w_t^{jr}, p_t^{e,jr}, \varkappa_t^{jr}, p_t^{jr}, c_t^{jr}, X_t^{jr}\}_{j=1,r=1}^{J,R}$, $\pi_t = \{\pi_t^{(jr)(j\tilde{r})}\}_{j=1,r=1,\tilde{r}=1}^{J,R,R}$, $s_t = \{s_t^{(jr)(\tilde{j})}\}_{j=1,\tilde{j}=1,r=1}^{J,J,R}$, such that the optimality conditions for workers and landlords –equations (1) and (7)–, intermediate varieties –equation (12)–, and final goods –equations (15) and (16)– hold and all markets clear –equations (17), (18) and (20).*

Definition 2. *Given $(L_0, S_{1,0}, S_{2,0}, \Upsilon_0, \{\Theta_t, \Phi_t\}_{t=0}^{\infty})$, a sequential competitive equilibrium is a sequence of $\{L_t, V_t, \mu_t, E_t^{f}, E_t, S_{1,t}, S_{2,t}, S_t, T_t, T_t^{r}, \Upsilon_t, Z_t\}_{t=0}^{\infty}$, where $V_t = \{V_t^{jr}\}_{j,r=1}^{J,R}$, $\mu_t = \{\mu_t^{(jr)(j'r')}\}_{j,j',r,r'=1}^{J,J,R,R}$, that solves the worker location decision –equations (4), (5) and (6)–, satisfies the energy and climate component –equations (11), (21), (22), (23), (25) and (26)– and solves the temporary equilibrium at each t.*

[18]There is no evidence on the existence of critical thresholds, also known as tipping points, beyond which the global climate system reorganizes abruptly or irreversibly (IPCC, 2021). However, for some extreme climate events, like heat waves, droughts or forest fires, there might be tipping points at the local scale.

[19]An alternative approach to modeling the heterogeneous world climate is to employ general circulation models, which describe the movements of air and water that are the drivers of local temperature. These models rely on a extremely large number of state variables.

3 Solution of the Model

The solution of an integrated assessment model with this rich spatial, industrial and dynamic structure requires pinning down a large number of fundamentals, which are not directly observable in the data. By writing the equilibrium conditions in time differences, I perform the quantitative analysis without estimating the level of the fundamentals of the economy (Dekle et al., 2007).

To ease the exposition, define $\dot{x}_{t+1} = x_{t+1}/x_t$ as the proportional change of variable x from period t to $t+1$. Given an allocation $(w_t, L_t, \pi_t, s_t, \varrho_t, S_{1,t}, S_{2,t}, \Upsilon_t)$, with $\varrho_t = \{\varrho_t^{jr}\}_{j=1,r=1}^{J,R}$ and $\varrho_t^{jr} = (p_t^{f,jr} e_t^{f,jr})/(p_t^{f,jr} e_t^{f,jr} + p_t^{c,jr} e_t^{c,jr})$ being the share of fossil fuel expenditure in the total energy use, a change of the state variables $(\dot{L}_{t+1}, \dot{S}_{1,t+1}, \dot{S}_{2,t+1}, \dot{\Upsilon}_{t+1}, \dot{\Theta}_{t+1})$, and a level of the exogenous climate variables Φ_{t+1}, the solution of $(\dot{w}_{t+1}, \dot{q}_{t+1}, \dot{p}^e_{t+1}, \dot{\varkappa}_{t+1}, \dot{p}_{t+1}, \dot{u}_{t+1}, X_{t+1}, \pi_{t+1}, s_{t+1})$ satisfies the system of equations displayed in Appendix B.2.

The solution of the temporary equilibrium in time differences resembles that of Caliendo et al. (2019) with two main differences. First, the presence of non-homothetic preferences with constant elasticity of substitution implies that the consumption shares evolve according to their previous values, the time difference of relative prices, and real income,

$$s_{t+1}^{(jr)(\tilde{\jmath})} = s_t^{(jr)(\tilde{\jmath})} \left(\frac{\dot{p}_{t+1}^{\tilde{\jmath}r}}{\dot{w}_{t+1}^{jr}}\right)^{1-\varsigma} \left(\dot{u}_{t+1}^{jr}\right)^{\vartheta^{\tilde{\jmath}}}, \quad \text{with} \quad \sum_{\tilde{\jmath}=1}^{J} s_{t+1}^{(jr)(\tilde{\jmath})} = 1.$$

The log-linear structure of the expenditure shares makes the solution in time differences particularly tractable. Moreover, it allows to decompose the temporal change of consumption shares into the component driven by variations in relative prices and that driven by changes in real income. Second, the evolution on the use of fossil fuels and clean energy depends on income, and the ratio of energy prices,

$$\dot{e}_{t+1}^{f,jr} = \left(\frac{\dot{w}_{t+1}^{jr} \dot{L}_{t+1}^{jr}}{\dot{p}_{t+1}^{f,jr}}\right) \left(\frac{\dot{p}_{t+1}^{f,jr}}{\dot{p}_{t+1}^{e,jr}}\right)^{1-\zeta}, \qquad \dot{e}_{t+1}^{c,jr} = \left(\frac{\dot{w}_{t+1}^{jr} \dot{L}_{t+1}^{jr}}{\dot{p}_{t+1}^{c,jr}}\right) \left(\frac{\dot{p}_{t+1}^{c,jr}}{\dot{p}_{t+1}^{e,jr}}\right)^{1-\zeta}.$$

In turn, the evolution of the energy composite price depends on the relative expenditure share of each energy source, as well as the evolution of the energy prices,

$$\dot{p}_{t+1}^{e,jr} = \left(\varrho_t^{jr} \left(\dot{p}_{t+1}^{f,jr}\right)^{1-\zeta} + (1-\varrho_t^{jr}) \left(\dot{p}_{t+1}^{c,jr}\right)^{1-\zeta}\right)^{1/(1-\zeta)}.$$

To ensure that the economic and climate variables converge to a steady state, I impose that the sequence of changes in fundamentals converges to one in the long-run, $\lim_{t\to\infty} \dot{\Theta}_{t+1} = 1$, and the exogenous emissions of carbon dioxide and the forcing of other greenhouse gases converge to zero over time, $\lim_{t\to\infty} \Phi_{t+1} = 0$. Given the structure of the energy and climate model, the aforementioned assumptions imply that global and local levels of temperature reach a steady state over time. Consequently, the damage function on productivity evaluated at local temperature, $\Omega^j(T_{t+1}^r)$, also converges to a constant value over time and the exogenous and endogenous variation of productivities converge to a constant value in the long-run.

Given data on $(w_0, L_0, \pi_0, s_0, \varrho_0, \mu_{-1}, S_{1,0}, S_{2,0}, \Upsilon_0)$, and a converging sequence of fundamental and exogenous climate variables $\{\Theta_{t+1}, \Phi_{t+1}\}_{t=0}^{\infty}$, the sequence of $\{\mu_{t+1}, L_{t+1}, \upsilon_{t+1}, S_{1,t+1}, S_{2,t+1}, T_{t+1}, T_{t+1}^r, \Upsilon_{t+1}\}_{t=0}^{\infty}$ solves the system of equations displayed in Appendix B.2, where $\upsilon_t = \{\exp(V_t^{jr})^{1/\nu}\}_{j=1,r=1}^{J,R}$

denotes a transformation of the value function. In addition to the equations characterizing the solution of the sequential equilibrium in time differences displayed in Caliendo et al. (2019), this solution must satisfy the energy and climate processes, given by equations (21), (22), (23), (26), and,

$$T_{t+1} = T_t + \lambda \log_2 \left(\frac{S_{t+1}}{S_t} \right) + \frac{\lambda}{\varphi} \left(F^x_{t+1} - F^x_t \right).$$

I briefly describe the algorithm to solve the model in time differences. For a further explanation, refer to Appendix B.6. First, I guess the path of CO_2 emissions and the time difference of the value function, $\{E^f_{t+1}, \dot{v}_{t+1}\}^{\mathrm{T}}_{t=0}$. Then, I compute the evolution of local temperature and the temporal change of the damage function, $\{T^r_{t+1}, \dot{\Omega}^j(T^r_{t+1})\}^{\mathrm{T}}_{t=0}$, as well as the migration shares and the employment levels $\{\mu_t, L_{t+1}\}^{\mathrm{T}}_{t=0}$. Then, I solve the temporary equilibrium in time differences, period by period, and obtain the level of global fossil fuel use and the time difference of utility, $\{E^f_{t+1}, \dot{u}_{t+1}\}^{\mathrm{T}}_{t=0}$. I solve backwards for the value function, $\{\dot{v}_{t+1}\}^{\mathrm{T}}_{t=0}$. Finally, if the difference between the guesses and the updated values for the path of carbon dioxide emissions and the temporal change of the value function are greater than a pre-specified tolerance, I iterate until convergence. Otherwise, the algorithm concludes.

4 Estimation of the Model

In this section, I construct initial data for consumption shares $s_0^{(jr)(\tilde{\jmath})}$, labor L_0^{jr}, wages w_0^{jr}, trade shares $\pi_0^{(jr)(j\tilde{r})}$, migration shares $\mu_{-1}^{(jr)(j'r')}$, fossil fuel and clean energy use $(e_0^{f,jr}, e_0^{c,jr})$, initial carbon stocks $(S_{1,0}, S_{2,0}, \Upsilon_0)$ and local temperature T_0^r. I set the exogenous paths for non-fossil fuel CO_2 emissions and non-CO_2 GHG forcing $\{E^x_t, F^x_t\}^{\infty}_{t=0}$. In addition, I estimate the following parameters, elasticity of substitution across goods ς, good-specific income elasticity $\vartheta^{\tilde{\jmath}}$, factor shares in valued added $(\alpha^L, \alpha^H, \alpha^E)$, share of value added in gross output ω^{jr}, materials share in non-value added $\omega^{(\tilde{\jmath}r)(jr)}$, trade elasticity θ, discount factor β, migration elasticity $1/\nu$, energy elasticity ζ, fossil fuel intensity η^{jr}, carbon circulation parameters (ψ_L, ψ_0, ψ), climate sensitivity λ and temperature downscaling factors g^r. Finally, I parametrize the extraction cost function $h(\cdot)$ in terms of cumulative fossil fuel use and identify the sector-specific damage function $\Omega^j(\cdot)$ in terms of local temperature.

4.1 Spatial and Industrial Resolution

The implementation of the solution method requires data of the initial period, which is considered as the 5-year window between 2011 and 2015. The industrial resolution of the model encompasses $J = 6$ economic sectors, namely, agriculture, industry (manufacturing, mining and utilities), construction, trade and transportation, finance, and government and other personal services.

The geographical resolution of the model considers $R = 287$ regions, which account for all countries in the world for which migration stocks are available. From them, 124 regions are individual countries and I group small countries into coarser geographical units (e.g., Caribbean Islands or Islands in Oceania). In addition, I disaggregate the six largest countries, in a geographical, economic and demographic sense, into their subnational units, since most of the commercial and immigration flows occur within, rather than across borders, and since wide countries tend to display large differences in climate conditions and industrial composition within their territory. More precisely, I decompose the United States into its 50 states and the District of Columbia, Canada into its 13 provinces and territories, China into its 31 provinces, India into

33 provinces, Brazil into its 26 states and the Federal District and Russia into 8 federal districts. Appendix A.1 delves into the precise definition of the geographical units used.

4.2 Preferences

To estimate the elasticity of substitution across goods, ς, and the good-specific income elasticity, $\vartheta^{\tilde{\jmath}}$, I follow the cross-country aggregate-level procedure of Comin et al. (2021). Specifically, I take the ratio of consumption shares, displayed in equation (7), for two different goods in a region and take logarithms to obtain,[20]

$$\log\left(\frac{s_t^{jr}}{s_t^{\tilde{\jmath}r}}\right) = \log\left(\frac{\gamma^j}{\gamma^{\tilde{\jmath}}}\right) + (1-\varsigma)\log\left(\frac{p_t^{jr}}{p_t^{\tilde{\jmath}r}}\right) + (\vartheta^j - \vartheta^{\tilde{\jmath}})\log\left(c_t^r\right) + \varepsilon_t^{jr}. \tag{27}$$

In the baseline specification, I estimate the preference parameters from the patterns of structural change in consumption. Unlike Comin et al. (2021), due to the presence of interregional trade, the relative sectoral consumption expenditures are not equal to the relative sectoral employment shares, so the left-hand side of equation (27) cannot be constructed using employment data. The first term in the right-hand side can be interpreted as a sector fixed effect and ε_t^{jr} is the estimating error. Hence, the estimation relies on the within-region country variation of consumption shares, relative prices and real income to identify the price and income elasticities. The identification assumption to obtain consistent estimates is that, for each region, the shocks to relative prices and income are uncorrelated with the relative demand shock ε_t^{jr}.

Data on current and constant consumption spending is taken from the OECD Final Consumption Expenditure of Households, which is an unbalanced panel ranging from 1950 to 2018 comprising country-level data for 38 OECD and 22 non-OECD countries. Consumption prices are constructed as the ratio of current to constant consumption spending and consumption shares are constructed based on nominal values. Data on country-level real income, c_t^r, is taken from the PWT database (Feenstra et al., 2015) and defined as the per capita expenditure-side real GDP at chained PPP in U.S. dollars.

Column (1) of Table 1 displays the baseline results of the estimation, taking as reference the industry sector and weighting observations by their population size. The price elasticity is less than unity, $\varsigma = 0.751$, implying that goods are complements. Relative to industry, the non-homotheticity parameter is significantly lower for agriculture, of roughly the same size for construction and trade and transportation, and significantly higher for finance and government and other services.[21] In the parametrization of the model, I normalize the income elasticity of the industry sector to one. Column (2) of Table 1 deems country-sector fixed effects. Columns (3) and (4), and (5) and (6) replicate columns (1) and (2) considering GDP weights and same weights, rather than population weights, across observations. Across the different specifications studied, the results do not vary qualitatively.

After estimating the parameters of the utility function, I construct the consumption shares of each good across all regions in the initial period. To do so, I supplement the OECD Final Consumption Expenditure of Households with the World Bank Global Consumption Database (WB, 2021), which is a cross-sectional database around the period 2000-2010, mostly focused on developing countries. In addition to providing

[20] For simplicity in the estimation of the preference parameters, I consider the region-aggregate consumption shares, rather than the sector-region consumption shares. The smaller the difference in income elasticities across sectors, the closer the approximation.

[21] These results are in line with those found by Comin et al. (2021) when considering a 10-sector classification (Table XII) and ignoring the presence of interregional trade. Goods are complements with a price elasticity of 0.1. The income elasticities of agriculture, construction, trade, transportation, finance, and other services are -0.68, 0.03, 0.62, 0.44, 1.17 and 0.18, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$1-\varsigma$	0.249	0.488***	-0.00618	0.499***	0.468***	0.407***
	(0.355)	(0.0784)	(0.331)	(0.0723)	(0.140)	(0.148)
$\vartheta^{\text{AGR}}-\vartheta^{\text{IND}}$	-0.602***	-0.488***	-0.743***	-0.603***	-0.369***	-0.353***
	(0.134)	(0.141)	(0.148)	(0.171)	(0.0533)	(0.0289)
$\vartheta^{\text{CON}}-\vartheta^{\text{IND}}$	0.264**	0.265**	0.162	0.170	0.316***	0.321***
	(0.103)	(0.126)	(0.108)	(0.155)	(0.0526)	(0.108)
$\vartheta^{\text{TRD}}-\vartheta^{\text{IND}}$	0.0696	0.159*	-0.0180	0.0848	0.219***	0.220***
	(0.0860)	(0.0821)	(0.103)	(0.0949)	(0.0414)	(0.0276)
$\vartheta^{\text{FIN}}-\vartheta^{\text{IND}}$	0.574***	0.436***	0.626***	0.384***	0.374***	0.417***
	(0.155)	(0.0418)	(0.178)	(0.0474)	(0.0883)	(0.0655)
$\vartheta^{\text{OTH}}-\vartheta^{\text{IND}}$	0.644**	0.430***	0.861**	0.447***	0.255*	0.437***
	(0.295)	(0.0530)	(0.338)	(0.0405)	(0.130)	(0.0657)
N	4,620	4,620	4,620	4,620	4,620	4,620
R^2	0.8230	0.9919	0.8463	0.9950	0.8234	0.9848
sector fe	X		X		X	
sector-country fe		X		X		X
weight pop	X	X				
weight GDP			X	X		
no weight					X	X

Standard errors clustered at the country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Estimation of the elasticity of substitution and the good-specific income elasticity.

information for 90 countries, it also contains data at the subnational-level for Brazil and India.

To perform the subnational disaggregation for the remaining countries, I resort to official national statistics and allocate the subnational information proportionally to preserve the national values.[22] To input consumption data for the 21 countries and the 8 subnational units of Russia with missing information, I pose that consumption spending is a sector-specific log-linear function on GDP per capita and population at the region-level.[23] Then, I employ the estimated coefficients to construct the consumption shares.

Appendix A.2 describes the details of the datasets and plots the spatial distribution of per capita consumption across goods and regions. In line with the estimation of the parameters in the utility function, agricultural goods tend to be mostly consumed by developing countries and services by developed countries. With data on the average consumption shares of good $\tilde{\jmath}$ in region r, $s_0^{\tilde{\jmath}r}$, I construct the consumption shares of good $\tilde{\jmath}$ of worker laboring in market jr, $s_0^{(jr)(\tilde{\jmath})}$, by targeting the values predicted by the log-linear extrapolation on GDP per capita and population so that the average value across economic sectors matches those observed in the data.

4.3 Technology

To calibrate the factor shares in value added, $(\alpha^L, \alpha^H, \alpha^E)$, I use standard values from the literature and set the share of labor to 65% (Tombe, 2015) and the share of energy to 4% (Golosov et al., 2014) for all regions

[22]For United States, the Consumer Spending by State from the Bureau of Economic Analysis. For Canada, the Detailed household final consumption expenditure data, provincial and territorial from the Statistics of Canada. For China, the People's Living Conditions of the Statistical Yearbook of Regional Economy.

[23]In the estimation, the coefficient of determination is higher than 0.9, so the fit is considered to be successful.

and sectors.[24] Gollin (2002) finds little variation in labor's aggregate share of value added across countries and Gollin et al. (2014) argue that since a country's employment share in agriculture does vary with income, the labor share of value added across sectors must be close to equal.

The share of value added in gross production, ω^{jr}, and the share of materials in non-value added, $\omega^{(\tilde{j}r)(jr)}$, target the input output linkages observed in the EORA dataset (Lenzen et al., 2012, 2013), so that market clearing conditions hold. The EORA dataset is a cross-section of national input output tables and bilateral trade information across 187 countries and 26 sectors from 1990 to 2015.[25] The global average values of these parameters are displayed in Table 2. The importance and source of intermediate inputs varies across sectors: industry has the highest share of materials in gross production and these goods are largely used in different industries.

	$(1-\omega^j)$	$\omega^{(\tilde{j})(j)}$					
		AGR	IND	CON	TRD	FIN	OTH
AGR	0.58	0.30	0.05	0.03	0.02	0.01	0.01
IND	0.31	0.43	0.70	0.58	0.29	0.17	0.33
CON	0.39	0.01	0.01	0.09	0.02	0.05	0.04
TRD	0.54	0.13	0.12	0.15	0.35	0.14	0.18
FIN	0.65	0.12	0.10	0.14	0.29	0.58	0.31
OTH	0.61	0.01	0.01	0.01	0.03	0.05	0.14

Table 2: Global average share of value added in gross production, $(1-\omega^j)$, and share of materials in non-value added, $\omega^{(\tilde{j})(j)}$.

To construct value added and employment for each sector, country, and subnational unit, I apply the following procedure. First, I obtain country-level information on real GDP (at chained PPP in U.S. dollars) and population from the Penn World Table version 10.0 (Feenstra et al., 2015). Then, I disaggregate value added and employment across economic sectors by means of the Structural Change Database (Szirmai and Foster-McGregor, 2017) and the Employment by Economic Activity Dataset of the International Labor Organization.

With sector- and country-level information, I refine the data at the subnational-level using official national statistics, maintaining the same aggregate values.[26] Appendix A.3 presents further details of the data and plots the spatial distribution of per worker value added. On average, value added per worker in the agriculture sector displays the lowest values relative to the other sectors. Although agriculture represents a large share of production and employment in the African continent, those countries exhibit the lowest value added per worker in the world. On the other extreme, value added per worker in the finance service shows the highest values in the United States, Canada, Europe, Oceania, and Middle East. Coastal Brazil,

[24] Cruz and Rossi-Hansberg (2021) estimate the energy share in value added to be 3.3%, Hassler et al. (2019) 5.55% and Krusell and Smith (2017) 6%.

[25] Other available sources to construct multi-region input output linkages are: World Input Output Database (Timmer et al., 2015b), OECD Input Output Database, GTAP (Aguiar et al., 2019) and EXIOBASE (Tukker et al., 2009). Nevertheless, I choose the EORA database due to its free access, its harmonized design across economic sectors, and its high regional resolution.

[26] Specifically, for United States, data is obtained from the GDP and Employment by State of the Bureau of Economic Analysis. For Canada, data is taken from the GDP by industry, provinces and territory from the Statistics of Canada and employment from the Census of 2016. For China, data is obtained from the Macro Economy and Labor Statistics Yearbooks. For India, value added is taken from States of India and labor from the Employment and Unemployment Surveys. For Brazil, value added is taken from the Brazilian Institute of Geography and Statistics and employment from the National Household Sample Survey Microdata. For Russia, Federal State Statistics Service.

northern India and mainland China exhibit low value added per worker in services relative to their national averages.

4.4 Trade Flows

To construct sector-specific bilateral trade flows across countries and subnational units, I apply the following procedure. First, I obtain data on international trade at the country-level from the EORA database.[27] Then, I collect information on subnational intranational and international trade from an extensive set of national statistics and custom data.

To illustrate the subnational decomposition, I use as example the United States. Intranational trade data across two subnational units in the United States is obtained from the Commodity Flow Surveys of 2012 and 2017. I construct the trade flows between two states as the product of the domestic absorption from the EORA database times the share of subnational trade relative to the national total from the Commodity Flow Surveys. International trade data from one subnational unit in the United States to another country, and vice versa, is obtained from the U.S. Census Bureau, 2011-2015. I allocate subnational trade data, maintaining the country-level aggregates as in the EORA database.

I repeat the procedure for Canada, where the Trade Data Online displays information on exports and imports of goods for each province in Canada relative to any other domestic province, country in the world and state in the United States; for China, where the Commodity Trade Database provides information on exports and imports of goods for each province in China relative to any domestic province and country in the world; for Russia, where Rutherford and Tarr (2006) provides information on exports and imports of goods and services for each federal district in Russia relative to any domestic federal district; and for Brazil, where the International Commerce Statistics provides information on exports and imports of goods for each state in Brazil relative to any other country in the world. A deeper discussion of the data sources is presented in Appendix A.4.

To proxy the missing subnational trade flows, mainly for the service sectors and the subnational units of India and the service sectors, I estimate,

$$X_t^{(jr)(j\tilde{r})} = \left(VA_t^{jr}\right)^{\beta_1} \left(VA_t^{j\tilde{r}}\right)^{\beta_2} \left(GDPpc_t^{r}\right)^{\beta_3} \left(GDPpc_t^{\tilde{r}}\right)^{\beta_4} \left(D^{r\tilde{r}}\right)^{\beta_5} \exp\left(\beta_6 \cdot \mathbb{1}_{\{r=\tilde{r}\}} + \iota_t + \varepsilon_t^{r\tilde{r}}\right). \tag{28}$$

This specification depends on sector-specific value added and GDP per capita for both the importer and exporter. In addition, I take into account the distance between two regions, $D^{r\tilde{r}}$. To construct this measure, I use the geographic location of more than 26,000 cities, construct the great circle distance between each pair of cities and aggregate the city-level bilateral distances at the region-level using population weights, as in Mayer and Zignago (2011). Finally, I incorporate a dichotomic variable capturing domestic trade, $\mathbb{1}_{\{r=\tilde{r}\}}$, and a year fixed effect, ι_t. I estimate equation (28) by Poisson Pseudo Maximum Likelihood (PPML) to alleviate any bias from the omission of zeros in observed trade flows, as suggested by Santos Silva and Tenreyro (2006), and employ the estimated coefficients to construct the missing trade flows.

Alternatively, I could have used country-level information from the EORA database, parametrize the trade costs and construct the estimated trade shares across subnational units. However, this approach imposes strong assumptions on the subnational trade flows. Hence, in order to replicate as closely as

[27] UN Comtrade presents information on international trade of goods, but excludes services sectors. To have a consistent measure of trade across industries, I utilize the EORA database, which displays information for all the countries considered in the quantification of this paper.

possible the data, I exhaust the available subnational trade information. Finally, I set the trade elasticity to be identical across sectors and equal to $\theta = 6$ (Eaton and Kortum, 2002; Simonovska and Waugh, 2014).[28]

4.5 Migration Flows

Reliable data on international migration flows, to measure the movement of people between countries over a given period, is scarce. In many countries, such data is not collected, as reporting systems are expensive, and the ones that collect them have different definitions of what constitutes a migrant in terms of the length or purpose of stay and might only consider formal migration movements. Therefore, missing and non-comparable data preclude an accurate measurement of the global migration patterns.[29]

Due to this limitation, a branch of the demographic literature (Abel, 2013; Abel and Sander, 2014; Azose and Raftery, 2019) has inferred migration flows from changes in bilateral migrant stock across periods. Migration stocks quantify the number of persons residing in each country at a particular point in time according to their place of birth. These measures can be collected, as they only require birthplace questions from a country's census or population survey.[30] I extend the methodologies developed by this strand of the literature to compute migration flows across countries, subnational units and working sectors, leading to a migration flow matrix of more than 1,700 markets of origin and destination.

The first step is to assemble the migration stocks across countries and then disaggregate them across subnational units. I mainly obtain the relation between country of residence and country of birth from the United Nations (UN, 2020). The data spans the period 1990 to 2015 at a five-year frequency. I supplement this dataset with the World Bank Bilateral Migration Stock (Özden et al., 2011) to enlarge the geographical coverage.

Then, I decompose the migration stocks at the subnational-level by resorting to microdata files of country's census or population survey for the years 1990, 1995, $\cdots$, 2015. To illustrate the subnational decomposition, consider the United States. Intra and international stock data for the United States comes from the American Community Survey, which informs the number of persons residing in each state that were born in each country of the world and each state of the United States. I allocate the subnational information, keeping the country-level information as in the United Nations and World Bank database.

I repeat the procedure for Canada using the Census of Canada and the National Household Survey Public Use Microdata, for China using the Census and Population Survey of China and Taiwan, for India using the Census of India, for Russia using Census of Russia and for Brazil using the Census of Brazil and the National Household Sample Survey Microdata. A deeper discussion of the data sources is presented in Appendix A.5.

To proxy the missing subnational migration stocks, across two subnational units in different countries, I estimate the gravity equation,

$$L_t^{br} = \left(\sum_{r'=1}^{R} L_t^{br'}\right)^{\beta_1} \left(\sum_{b'=1}^{R} L_t^{b'r}\right)^{\beta_2} \left(\sum_{r'=1, r'\neq b}^{R} L_t^{br'}\right)^{\beta_3} \left(\sum_{b'=1, b'\neq r}^{R} L_t^{b'r}\right)^{\beta_4}$$

[28] Caliendo and Parro (2014) provide sector-specific trade elasticities for agriculture and industries, but not for services. The trade elasticity in agriculture is larger than in industry.

[29] Although some projects seek to correct and harmonize migration flows for a subset of developed countries (Raymer et al., 2013), its restrictive spatial coverage of developed countries prevents a global analysis of migration patterns.

[30] Abel and Cohen (2019) surveys and compares the accuracy of different methods to infer migration flows. The method developed by Azose and Raftery (2019) outperforms the other procedures.

$$\cdot \left(GDPpc_t^b\right)^{\beta_5} \left(GDPpc_t^r\right)^{\beta_6} \left(D^{br}\right)^{\beta_7} \exp\left(\beta_8 \cdot \mathbb{1}_{\{b=r\}} + \iota_t + \varepsilon_t^{br}\right). \tag{29}$$

where L_t^{br} denotes the number of person born in b residing in r. This specification depends on the population in the place of birth, the place of residence, the number of persons residing in a different place, the number of persons who were born in a different place, the GDP per capita of both the place of birth and residence. In addition, I consider a measure of distance, D^{br}, a dichotomic variable capturing the number of stayers, $\mathbb{1}_{\{b=r\}}$, and a year fixed effect, ι_t. After estimating this equation by PPML and completing the matrices of migration stocks, I decompose the place of residence into the market of residence by using the share of workers in each industry from the ILO database.

Then, I extend the procedure outlined in Azose and Raftery (2019) to infer the migration flows from changes in the migration stocks of two consecutive periods and demographic data. A brief description of the methodology is presented below and a rigorous description is presented the Appendix B.5. First, I control for deaths and births to guarantee that changes in the migration stocks reflect movements across regions, rather than natural population changes. Thus, for each place of birth, the number of workers in each market from the beginning and end of a 5-year period is known. In other words, I know the marginal totals of the migration flows, but need to estimate the entries of the migration tables. Migration flows are assumed to follow a Poisson process, where the mean is parametrized as the interaction of a combination of market fixed effects. The solution of the Maximum Likelihood estimates only requires information on marginal totals of the migration flows and an assumption of the number of stayers. Since imposing minimum mobility might not be a realistic assumption, I consider a weighted average of the estimates of minimum migration and a model that does not distinguish between migrants and stayers to compute migration flows across more than 1,700 markets.

Figure 1 illustrates the mobility patterns at the global scale from 1995 to 2015. The left panel shows that between 12% to 13% of households stay in the same region, but switch to a different sector. The spatial mobility displays higher frictions, as 3% of households migrate to a different place but work in the same sector, and only 1% move to both a new location and industry. The right plot depicts the mobility across economic sectors. The large majority of agriculture workers stay in the same sector, but those who switch, move to trade and transportation and industry. A minuscule number of workers switch from agriculture to finance.

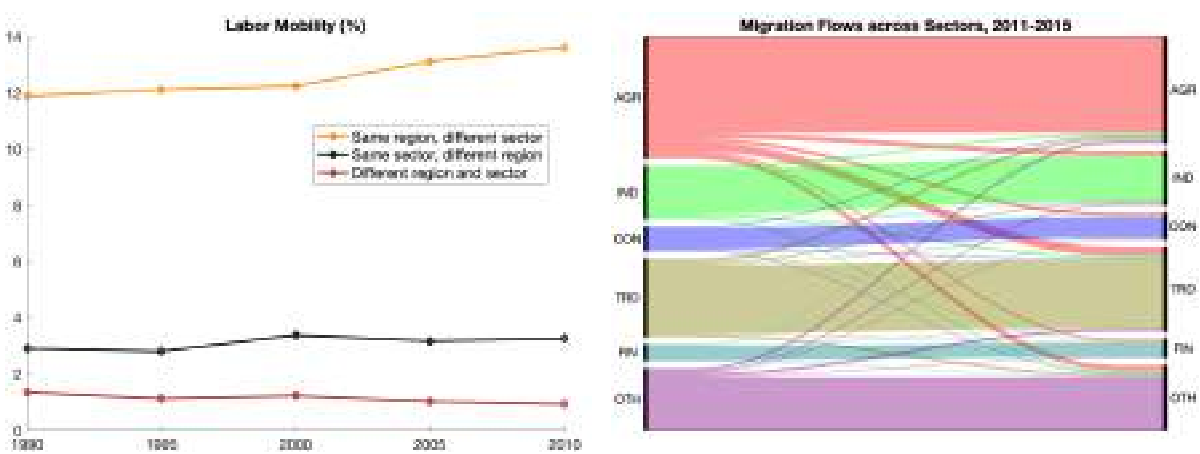

Figure 1: Global migration patterns.

4.6 Migration Elasticity

The procedure to identify the migration elasticity is based on the work by Artuç and McLaren (2015) and Caliendo et al. (2021). The estimation method relies on the migration shares, given by equation (6), and the Bellman equation,

$$V_t^{jr} = \log(B_t^{jr} c_t^{jr}) + \beta V_{t+1}^{jr} - \chi_t^{(jr)(jr)} + \Lambda_t^{jr}, \tag{30}$$

$$\Lambda_t^{jr} = \nu \log \left(\sum_{j'=1}^{J} \sum_{r'=1}^{R} \exp \left(\beta \left(V_{t+1}^{j'r'} - V_{t+1}^{jr} \right) - \chi_t^{(jr)(j'r')} \right)^{1/\nu} \right), \tag{31}$$

where Λ_{t+1}^{jr} denotes the option value of migration.[31] This procedure comprises two steps: First, the Poisson regression stage, where the value functions V_t^{jr} are estimated up to a constant. Second, the Bellman equation stage, where the parameter ν is identified using the estimates of the previous step. Appendix B.3 delves into the derivation of the estimating equations. Hereinafter, I assume that the migration costs are time-invariant, $\chi_t^{(jr)(j'r')} = \chi^{(jr)(j'r')}$.

In the first stage, I manipulate the mass of workers migrating across markets and use the definition of the option value of migration to arrive at the following equation,

$$\begin{aligned} \mu_t^{(jr)(j'r')} L_t^{jr} &= \exp \left(\mathcal{D}_t^{j'r'} + \mathcal{O}_t^{jr} - \frac{1}{\nu} \chi^{(jr)(j'r')} \right) + \xi_t^{(jr)(j'r')}, \\ \mathcal{D}_t^{j'r'} &= \frac{\beta}{\nu} (V_{t+1}^{j'r'} - V_{t+1}^{11}), \\ \mathcal{O}_t^{jr} &= -\frac{\beta}{\nu} (V_{t+1}^{jr} - V_{t+1}^{11}) + \log \left(L_t^{jr} \right) - \frac{1}{\nu} \Lambda_{t+1}^{jr}, \end{aligned} \tag{32}$$

where $\mathcal{D}_t^{j'r'}$ is a destination-time fixed effect, $\mathcal{O}_t^{jr}$ is an origin-time fixed effect, $\chi^{(jr)(j'r')}/\nu$ is a time-invariant fixed effect, and $\xi_t^{(jr)(j'r')}$ is the sampling error. The terms $\mathcal{D}_t^{j'r'}$ and $\mathcal{O}_t^{jr}$ are separately identified, since $\mathcal{D}_t^{11} = 0$. Equation (32) is estimated by PPML.

The second stage formulates the Bellman equation as an estimating equation using the destination- and origin-time fixed effects, $\mathcal{D}_t^{j'r'}$ and $\mathcal{O}_t^{jr}$, of the previous step. To construct the estimating equation, I employ equation (30) of period $t+1$ and substitute out the option value of migration Λ_{t+1}^{jr} using the definition of the destination- and origin-time fixed effects,

$$\mathcal{D}_t^{jr} + \beta \mathcal{O}_{t+1}^{jr} - \beta \log(L_{t+1}^{jr}) = \frac{\beta}{\nu} \left(\beta V_{t+2}^{11} - V_{t+1}^{11} \right) - \chi^{(jr)(jr)} + \frac{\beta}{\nu} \log \left(B_{t+1}^{jr} u_{t+1}^{jr} \right) + \varpi_t^{jr}. \tag{33}$$

In equation (33), the variable in the left-hand side is constructed with the results of the first stage and data on population. The first term on the right-hand side is a time fixed effect, the second term is a time-invariant market-specific fixed effect, and the last term is the regression residual.

The identification strategy can be understood as follows: The first stage uses the observed migration flows to infer the *pull*, $\mathcal{D}_t^{jr}$, of each market at every period, which is a combination of the future relative profitability of each market and the workers' responsiveness, β/ν. With a panel of such *pull* estimates and real income, in the second stage I estimate the extent to which the pull is affected by changes in real income. This allows me to separate out the responsiveness β/ν.

[31] Since the idiosyncratic shocks are drawn according to a Gumbel distribution with mean zero and standard deviation proportional to ν, Artuc et al. (2007) show that the option value of migration can be written as in equation (31).

As discussed by Artuç et al. (2010), the disturbance term might be correlated with the regressor. Hence, I employ the two-period lagged values of real income as instruments. In line with Nordhaus (2017), I set a discount rate of 1.5% per year, implying a value of $\beta = (0.985)^5$.[32] Regarding the structure of amenities, B_t^{jr}, I seek to be as general as possible and thus consider a flexible set of parametrizations, defined as the combination of a global time-fixed effect, a market-specific time-invariant fixed effect, a sector-specific linear time trend, and a region-specific linear time trend.

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$1/\nu$	0.106***	0.0565*	0.0735***	0.0735***	0.151***	0.208***	0.119***	0.123
	(0.0263)	(0.0313)	(0.0264)	(0.0264)	(0.0289)	(0.0362)	(0.0298)	(0.0795)
Observations	6,884	6,884	6,884	6,884	6,876	6,876	6,876	6,876
R^2	0.8864	0.8999	0.8885	0.8885	0.8868	0.9008	0.8890	0.9159
$B_t^{jr} = B_t B^{jr}$	X				X			
$B_t^{jr} = B_t B^{jr} \exp(b^r t)$		X				X		
$B_t^{jr} = B_t B^{jr} \exp(b^j t)$			X				X	
$B_t^{jr} = B_t B^{jr} \exp(b^{jr} t)$				X				X

Standard errors clustered by region in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Sensitivity analysis for the migration elasticity $1/\nu$.

Table 3 shows the estimation of the migration elasticity for different parametrizations of the amenity component and stances on real income. The instrumental approach suggests that the migration elasticity lies between 0.12 and 0.21. I take $1/\nu = 0.15$ as my baseline estimate. Since I consider a larger discount factor and a quinquennial window of time, rather than an annual window, it is natural to obtain lower values for the migration elasticity relative to the literature (Caliendo et al., 2019, 2021),[33] since over longer periods of time most of the migration movements are returns to the place of birth and the influence of income is smaller.

4.7 Energy

To construct sector-specific energy use of fossil fuels (carbon, oil and natural gas) and clean energy (nuclear energy, hydroelectricity and renewables) across countries and subnational units, I apply the following procedure. First, I obtain country-level data on fossil fuels, measured in tons of CO_2, from the Emissions Database for Global Atmospheric Research (EDGAR) (Crippa et al., 2019) and IEA (2020a). I take country-level data on clean energy from BP (2019). Then, I collect data from national statistics to decompose across subnational units, keeping the aggregates as observed in the aforementioned sources.[34] Appendix A.6

[32] Stern (2006) adds moral arguments in the determination of the discount rate: future generations should be valued as much as current generations. Therefore, he chooses a very small discount rate of 0.1% per year, entailing a discount rate of $\beta = (0.999)^5$.

[33] Caliendo et al. (2019) analyze the migration movements across industries and states within the United States. Caliendo et al. (2021) study the migration movements across industries and countries within the European Union. Using a yearly discount factor between 0.96 and 0.97, these studies obtain a migration elasticity of roughly 0.5.

[34] For United States, I employ data from the U.S. Energy Information Administration; for Canada, the Canada's Official Greenhouse Inventory and Electric Power Generation; for China, the Energy and Environmental Statistics Yearbook; for India, the Greenhouse Gases Platform India; for Brazil, Greenhouse Gases Emission and Removal System. Data on clean energy for India and Brazil at the subnational-level is not available. So, I use the same disaggregation as that for fossil fuels. For Russia, I take the information from Xiao et al. (2021).

delves into the details of the datasets and plots the spatial distribution of per capita energy use. Energy use per capita is highly correlated with GDP per capita. Northern Africa, Middle East and North of China display a relatively large use of fossil fuels, due to the abundance of such resource. Scandinavia and Canada are relatively more intensive in clean energy. Finally, I employ data from IEA (2020b) to allocate the total energy use across economic sectors. Industry and trade and transportation are the sectors using most of the energy, together they consume more than 90% of the total energy.[35]

The elasticity of substitution across energy types, ζ, is set to 1.6 (Popp, 2004).[36] I follow Acemoglu et al. (2019) and consider that the relative price between clean and dirty energy sources equals 1.15. Using this parametrization and the optimality conditions between energy types, I derive the value of the fossil fuel intensity in energy generation, η^{jr}. I parametrize the cost of extracting fossil fuels, $h(\cdot)$, in terms of the cumulative use of this resource, as in Cruz and Rossi-Hansberg (2021). They employ data from Rogner (1997) and Bauer et al. (2017) to derive this function. More precisely, they restrict the total stock of fossil fuels in the ground to match the total carbon dioxide emissions in the next five centuries in the RCP 8.5 scenario from IPCC (2013).

4.8 Carbon Circulation and Climate

In order to model the carbon depreciation, I use the structure proposed in Golosov et al. (2014), where $\psi_L = 0.2$ denotes the share of carbon emitted into the atmosphere, $1 - \psi_0 = 1 - 0.4019$ the share of emissions exiting the atmosphere immediately, and $\psi = 0.0115$ the depreciation rate of CO_2 every period.[37] The forecast of the exogenous flow of carbon dioxide emissions, E_t^x, is taken from the RCP 8.5 scenario of the RCP Database version 2.0. According to historical data on carbon dioxide emissions by Meinshausen et al. (2011), the carbon stocks for the year 2000 take the values of $S_{1,0} = 2,572.38$ $GtCO_2$ and $S_{2,0} = 460.62$ $GtCO_2$.[38] I follow Nordhaus (2017) and set the climate sensitivity to $\lambda = 3$.[39]

Since I pursue a fine level of spatial disaggregation, I need to derive the evolution of local climate based on global conditions. To this end, I employ the statistical downscaling method of Mitchell (2003), implemented by Cruz and Rossi-Hansberg (2021). They estimate the local downscaling factor g^r at a level of resolution of $1° \times 1°$ (around 110km by 110km in the Equator) based on geographical attributes of each cell. On average, arctic regions warm 2.5 times faster than the global average, whereas tropic and inland areas warm 66% slower than the global average. I aggregate these coefficients at the country- and subnational-level using population weights from the Gridded Population of the World version 4 for the year 2000.

[35] More precisely, the shares of energy use across sectors are: industry (75.39%), trade and transportation (17.09%), agriculture (3.39%), government and other services (2.45%), finance (0.87%) and construction (0.82%). Since industry encompasses mining, quarrying, manufacturing of oil and gas, this sector embodies the largest share of energy use.

[36] In the long-term, this elasticity of substitution might be larger, due to the reduction of the cost of clean energy storage and the development of hybrid cars.

[37] The calibration of these parameters is based on the following facts: 20% of any emission pulse will stay in the atmosphere for a thousand years, $\psi_L = 0.2$. The excess of carbon that does not stay in the atmosphere *forever* has a mean lifetime of 300 years, $(1 - \psi)^{60} = 0.5$ with $\psi = 0.0115$. About half of the CO_2 pulse to the atmosphere is removed after a time scale of 30 years, so $\delta_6 = 0.2 + 0.8\psi_0(1 - 0.0115)^6 = 0.5$ and $\psi_0 = 0.4019$.

[38] The permanent layer is constructed as the sum of the carbon accumulation in the pre-industrial era plus a fraction ψ_L of the total emissions up to the initial period. The slowly depreciating layer is residually calculated as the difference between the total carbon stock in the atmosphere minus the permanent layer.

[39] Despite substantial research on this topic, climate sensitivity estimates have remained uncertain. IPCC (2021) estimates that the climate sensitivity lies between 2 and 4.5 with more that 66% probability.

Local temperature, T_0^r, for the initial period is constructed as in Dell et al. (2012). I obtain weather data from the Terrestrial Air Temperature and Precipitation, Version 5.01 (Matsuura and Willmott, 2018). This dataset provides gridded monthly temperature, measured in degrees Celsius at a spatial resolution of $0.5° \times 0.5°$ degrees. I employ annual temperature and aggregate cells into countries and subnational units using population weights.

4.9 Damage Function

To parametrize the sector-specific damage function, $\Omega^j(\cdot)$, I construct a long panel on value added productivity and use a fixed effect model to identify the causal effect of temperature on productivity. Finally, to lend credibility of the main results, I perform a series of robustness exercises.

Following equation (8), measured value added productivity is defined as the ratio of real value added to its inputs, namely labor, land and energy, which are aggregated in a Cobb Douglas fashion with Constant Returns to Scale. In the description of the model, I consider land to be time-invariant at the region-level. Due to the large time horizon over which global warming might operate, in this subsection I account for changes of this production factor over time. Henceforth, I use a broader definition of land, as one which adds capital accumulation.

In an open economy, measured productivity captures two forces: the fundamental productivity that firms would have under autarky and the additional productivity arising from specialization or trade selection. As argued by Caliendo et al. (2017) and Uy et al. (2013), I can retrieve the fundamental productivity using the measured productivity times the domestic absorption ratio raised to the inverse of the trade elasticity. With the aforementioned definition, I construct a dataset of sector- and region-specific fundamental value added productivity ranging from 1950 to 2017. Below, I briefly describe the data and the construction of the variables. Further details are presented in Appendix A.8.[40]

Real value added and employment are mainly taken from the GGDC 10-sector (Timmer et al., 2015a) and the OECD STAN database (OECD, 2020). To enlarge the spatial coverage, I supplement these datasets with continent- and country-specific information, namely, EU KLEMS database (O'Mahony and Timmer, 2009), Expanded Africa Sector Database (Buadi and Szirmai, 2018), Asian Productivity Organization database (APO, 2020), Bureau of Economic Analysis, and Current Population Survey.

Capital stock is computed through the perpetual inventory method, as outlined in Inklaar et al. (2019). Investment data, for all the countries in the world, is taken from the Capital Details of the PWT dataset. Since capital stock provides a larger weight to long-lived assets relative to short-lived assets, I construct capital services as a chain-type index of the services flows derived from different assets, where the weights depends on the capital rental prices.

Energy is a CES composite between fossil fuels and clean sources. The methodology and datasets employed in its construction are the same as those described in Section 4.7. Trade data from Section 4.4 provides an accurate description of the cross-section for a short period of time. Thus, I employ such data for the year 2015 and extrapolate to the past using the growth rates of the domestic absorption ratio from the

[40] An alternative approach to estimate the effect of temperature on productivity is to condition on observable data, invert the economic model to retrieve the fundamental productivity and use weather fluctuations to identify the effect of temperature on productivity, as performed in Rudik et al. (2021). Since the identification strategy emphasizes the variation over time within a given market, the temporal dimension of the panel needs to be sufficiently large. The absence of data on trade and migration for a large number of periods for all regions considered, particularly for developing countries, precludes the use of this approach in a worldwide setting.

Trade Details of the PWT.

The aforementioned datasets allow me to construct an unbalanced panel of value added productivity ranging from 1950 to 2017 across the six economic sectors of interest. Due to data limitations, the panel does not comprise all the geographical units considered in Section 4.1. However, since the panel considers a large set of both developed and developing countries, I have information across the whole spectrum of temperatures and income.

I identify the causal effect of temperature on fundamental value added productivity using a panel fixed-effects model with weather variables entering the regression in a non-linear fashion. Specifically, I parametrize the damage function as,

$$\log(\Omega^j(T_t^r)) = \tau_1^j \cdot T_t^r + \tau_2^j \cdot (T_t^r)^2 + \rho_1^j \cdot P_t^r + \rho_2^j \cdot (P_t^r)^2 + \iota^{jr} + \iota_t^{jc} + \gamma_1^{jr} \cdot t + \varepsilon_t^{jr}, \tag{34}$$

in terms of local temperature, T_t^r, precipitation, P_t^r, and a combination of fixed effects and time trends, where r indexes regions and c continents, as defined in (Dell et al., 2012). In line with Burke et al. (2015), productivity accounts for (i) time-invariant differences between markets, ι^{jr}, like culture, history, natural or geographical attributes;[41] (ii) contemporaneous shocks at the sector- and continent-level, ι_t^{jc}, such as changes in prices or technological innovations; (iii) country-specific linear growth trends, $\gamma_1^{jr} \cdot t$, which might arise from slowly changing factors within a market, such as demographic shifts, trade liberalizations, political institutions or economic policies;[42] and (iv) the possibility for non-linear effects of local annual average temperature and precipitation, where historical weather data are constructed with information from Matsuura and Willmott (2018).[43]

More specifically, the damage function is an additive separable second order polynomial in temperature and precipitation, implying heterogeneous effects of warming depending on the current level of temperature. As a robustness exercise, I consider higher order polynomials. For most of the temperature spectrum, the results are robust. However, the estimation is sensitive at high temperatures, which are key in the projection of welfare losses when temperature rises beyond the current observations. Alternatively, I could have employed a non-parametric approach as in Cruz and Rossi-Hansberg (2021) to infer the shape of the damage function. Unfortunately, such methodology requires a huge number of observations to provide accurate results.

Equation (35) denotes the marginal warming damage, which can be interpreted as the percentage change on productivity when local temperature rises 1°C,

$$\frac{\partial \log(\Omega^j(T_t^r))}{\partial T_t^r} = \tau_1^j + 2 \cdot \tau_2^j \cdot T_t^r. \tag{35}$$

I expect the intercept to be positive, $\tau_1^j > 0$, and the slope to be negative, $\tau_2^j < 0$, so that warmer temperatures benefit cold regions, but harm hot locations. In this sense, the non-linear functional form suggests the presence of an optimal temperature level, $\mathcal{T}^{j,*}$, which occurs when the marginal damage equals zero.

[41] These fixed effects ensure that the model is estimated on deviations from market averages, rather than on cross-sectional differences in climate, which might correlate which average productivity. One of the main drawbacks of a cross-sectional estimation is the omitted variable bias. A panel methodology solves this concern.

[42] Time fixed effects and linear trends account for potentially correlated trends in both temperature and productivity that are shared across the sample.

[43] To the extent that temperature and precipitation are spatially correlated, the omission of precipitation in the estimation would bias the coefficients on temperature, as the error term would be correlated with the regressor of interest.

The combination of fixed effects, time trends and covariates defines the identification strategy: after controlling for these factors, deviations in weather are as good as random (Hsiang, 2016). This identification strategy has been extensively used after the pioneering work of Deschênes and Greenstone (2007). I estimate equation (34) in one year time differences to account for any additional time invariant factors, weight spatial units by population size and cluster the error term by country and year-continent, as in Dell et al. (2012). Table 4 displays the results of the main specification across 6 economic sectors.

	Agriculture	**Industry**	**Construction**	**Trade and Transportation**	**Finance**	**Government and Others**
τ_1^j	2.998**	1.339	3.510**	2.238*	0.108	0.858
	(1.268)	(1.344)	(1.451)	(1.271)	(1.384)	(0.746)
τ_2^j	-0.143***	-0.0615	-0.144**	-0.0909**	0.0163	-0.0340
	(0.0368)	(0.0472)	(0.0602)	(0.0447)	(0.0529)	(0.0302)
ρ_1^j	0.132**	0.00507	0.0261	-0.00651	0.0820	0.0129
	(0.0660)	(0.0392)	(0.0531)	(0.0278)	(0.0576)	(0.0210)
ρ_2^j	-0.000402**	-0.0000552	-0.000140	-0.0000311	-0.000246*	-0.0000753
	(0.000176)	(0.000114)	(0.000153)	(0.0000827)	(0.000147)	(0.0000706)
N	4,765	4,736	4,771	4,700	4,716	4,737
R^2	0.315	0.441	0.371	0.477	0.334	0.487
$\mathcal{T}^{j,*}$	10.50	10.89	12.21	12.31	-3.32	12.61

Standard errors clustered by country and year-region, as defined by Dell et al. (2012), in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect of temperature and precipitation on productivity across economic sectors.

Agriculture and construction stand out as the most climate sensitive sectors, since they display significant and large coefficients. The left panel of Figure 2 shows the point estimates of the damage function of temperature on productivity for the agriculture sector, its 90%, 95% and 99% confidence intervals, and the effect for a selected number of countries, namely, Mongolia (MNG), Russia (RUS), Canada (CAN), United States (USA), China (CHN), Brazil (BRA), India (IND), and Burkina Faso (BFA). For countries with yearly average temperatures close to zero Celsius, like Mongolia, agricultural productivity is expected to increase by roughly 3% when local temperature rises one degree Celsius. The beneficial effects of rising temperatures vanish when moving to warmer places, until they reach zero and eventually turn into damages. Hence, an increase in local temperature of one degree Celsius in the hottest countries of the world, like Burkina Faso, diminishes productivity by more than 6%.[44] Agriculture is significantly affected by the level of precipitation, although the coefficients on precipitation are an order of magnitude lower with respect to those of temperature, as argued by Schlenker and Roberts (2009).

Relative to agriculture and construction, trade and transportation exhibit lower and significant climate sensitivities. Relative to trade and transportation, industry displays smaller and non-significant responses to warming.[45] Lastly, finance, government and other services display no significant impact of temperature on productivity, as illustrated in the right panel of Figure 2. Conforming with intuition, sectors mostly performed outdoors undergo a higher climate sensitivity, as shown in Figure 3.[46]

[44]Confidence intervals widen at extreme temperatures, since there are fewer observations at these values.

[45]When decomposing the industry sector, manufacturing presents significant warming effects, in order of magnitude similar to those of trade and transportation. In contrast, mining and utilities show no significant results.

[46]Lab experiments, surveyed by Seppanen et al. (2003), suggest that there is a general detriment in cognitive and physical perfor-

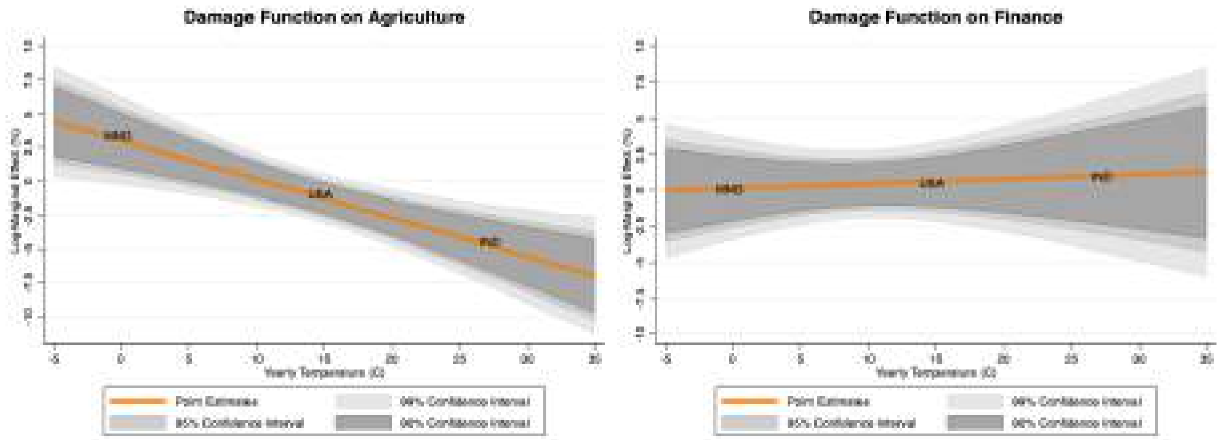

Figure 2: Marginal damage function of temperature on agriculture and finance.

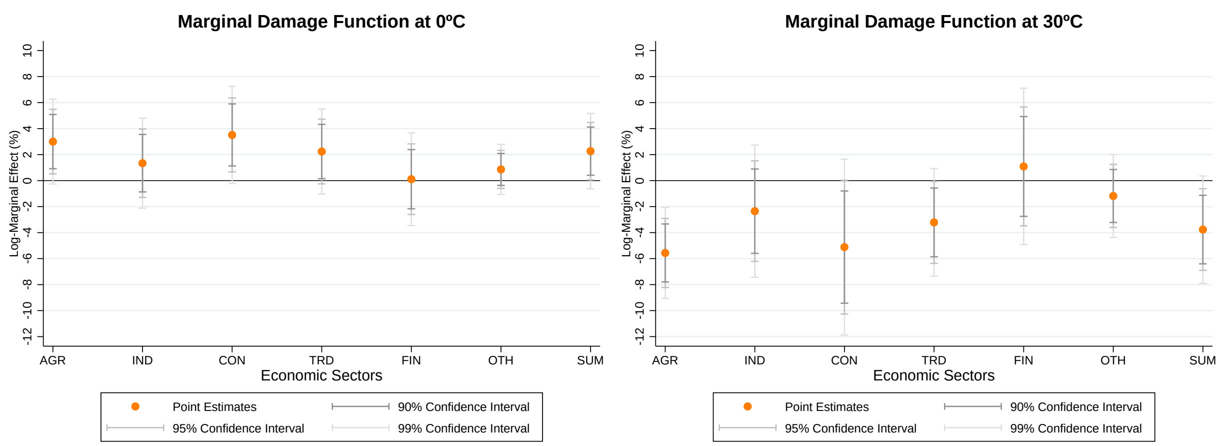

Figure 3: Marginal damage at 0°C and 30°C across different sectors.

When estimating the damage function for the aggregate economy, the coefficients of interest take the values of $\tau_1 = 2.265$ (1.127) and $\tau_2 = -0.101$ (0.0419), indicating that the optimal temperature, in a one-sector economy, is 11.26°C. This result is in line with the literature: Cruz and Rossi-Hansberg (2021) estimate the bliss point for winter temperature to be 1.6°C, with global winter temperature being roughly 10°C lower than its yearly average, Burke et al. (2015) find that country-level aggregate economic production is maximized at 13°C, and Nordhaus (2006) uses gridded data of output and finds an optimal temperature between 8°C and 14°C.

Equation (34) imposes that the marginal damage function is specific for each sector, through the coefficients (τ_1^j, τ_2^j), and country, through the level of temperature. In this sense, such specification restricts additional heterogeneity that might occur at the cross-country level. Moreover, such specification might also abstracts away from the potential adaptation mechanisms, for instance, richer countries might be better suited to attenuate the warming effects on productivity relative to poor countries. Henceforth, to verify that the results are not driven by the choice of the functional form or the covariates employed, I perform several robustness exercises to the main specification. Below I briefly describe the main results and Appendix A.8 delves into the estimation.

mance when temperatures exceeded certain thresholds.

I test the sensitivity of the empirical results by interacting temperature with income and higher order moments of the temperature distribution. Specifically, the 30-year rolling averages of real GDP, average temperature, temperature range (difference between the maximum and minimum yearly temperature), standard deviation and skewness of temperature. In addition, I incorporate additional covariates, like lagged values of temperature, and extend the polynomial to a cubic one. To test for potential growth effects, I apply the framework specified in Dell et al. (2012), that is, I consider that both the level and the growth rate of productivity are functions of weather conditions. Across all these specifications, the coefficients of interest, (τ_1^j, τ_2^j), display similar values, the additional regressors display non significant results and the power of the estimation tends to be lower. Consequently, my preferred specification is equation (34). Lastly, I perform a placebo exercise to understand whether current productivity reacts to future (one-year ahead) changes in temperature. The results are non significant.

Summarizing, global warming is expected to have heterogeneous effects on productivity across sectors. Agriculture and construction are the most climate sensitive, with cold regions benefiting from this phenomenon, while hot regions are hurt.

4.10 Productivities and Amenities

I estimate the time difference of the non-climatic component of productivity for each sector-region pair, $\{\dot{A}_{t+1}\}_{t=0}^{\mathrm{T}}$, so that for each market the growth rate of utility in the model targets the average growth rate of real value added per capita observed in the data from 1990 to 2015. I set the time difference of productivity in the generation of fossil fuels and clean energy, $\{\dot{A}_{t+1}^f, \dot{A}_{t+1}^c\}_{t=0}^{\mathrm{T}}$, to be constant across sectors and regions, and project them so that the growth rate of global CO_2 emissions and clean energy use in the model match the average growth rates observed in the data from 1990 to 2015, respectively. I estimate the time difference of amenities for each sector-region pair, $\{\dot{B}_{t+1}\}_{t=0}^{\mathrm{T}}$, so that the future migration flows are identical to those observed in the data in the initial period. After 100 periods, both productivities and amenities remain constant, so that the economy achieves a steady state. In the baseline estimation, I consider that the migration and commercial frictions take the same values as those observed in the initial period. Appendix A.9 discusses the estimation of these variables.

5 Results

The quantitative results of the model are organized as follows: First, I describe the evolution of climate variables. Then, I discuss the heterogeneous welfare effects across regions and sectors. Finally, I evaluate the extent of sectoral reallocation as a consequence of global warming.

5.1 Climate Variables

Figure 4 displays, in its left panel, the projections for CO_2 emissions. For comparison, the plot also presents the estimates in the two most pessimistic scenarios of IPCC (2013), namely, the Representative Consumer Pathways 8.5 and 6.0. As for the carbon flow, it increases from 35 $GtCO_2$ in 2015 throughout the next century until it reaching a peak of roughly 112 $GtCO_2$ per year. Afterwards, it decreases towards zero as a consequence of the sharp increase in the extraction cost of fossil fuels.

The right panel shows the evolution of global temperature, expressed in degrees Celsius, relative to its pre-industrial level. The higher level of carbon emissions rises the atmospheric concentration of CO_2

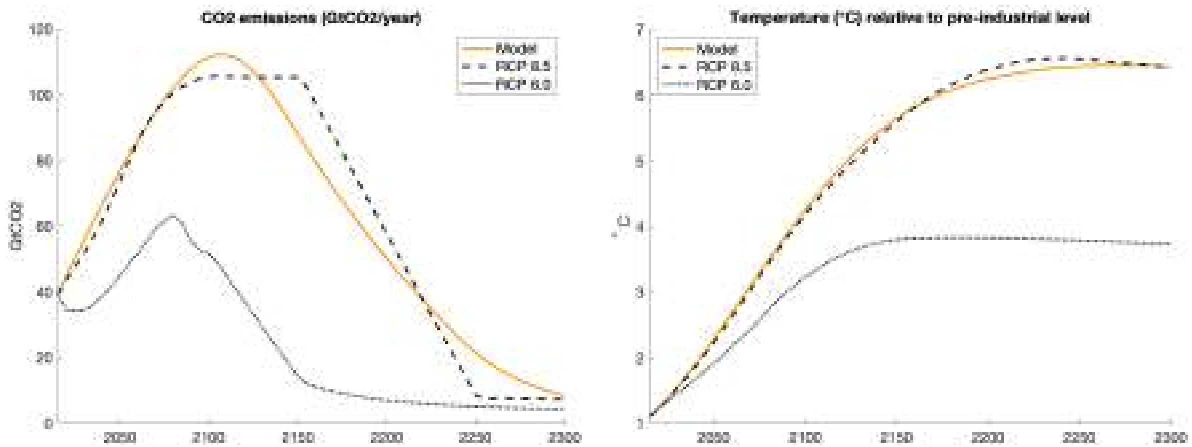

Figure 4: CO_2 emissions and global temperature.

and, thus, the global temperature. Since carbon depreciates slowly, the effects of carbon dioxide in the atmosphere are long lasting. By the end of the current century, global temperature is expected to be 4.2°C higher compared to its pre-industrial level. By the end of the next century, this value rises to 6.2°C. This result is in line with the most pessimistic scenario of IPCC (2013).

The aforementioned path for global temperature is projected to have differentiated effects over space on local climate conditions. Figure 5 compares the levels of temperature for the years 2015 and 2215. In the initial period, Central Africa experienced temperatures close to 30°C, whereas the Northern provinces of Canada and Russia faced temperatures between -10°C and -3°C. Two centuries later, most of the tropical zones are expected to experience temperatures between 32°C and 34°C. On the other extreme, the coldest places in the Earth are predicted to have temperatures above 0°C.

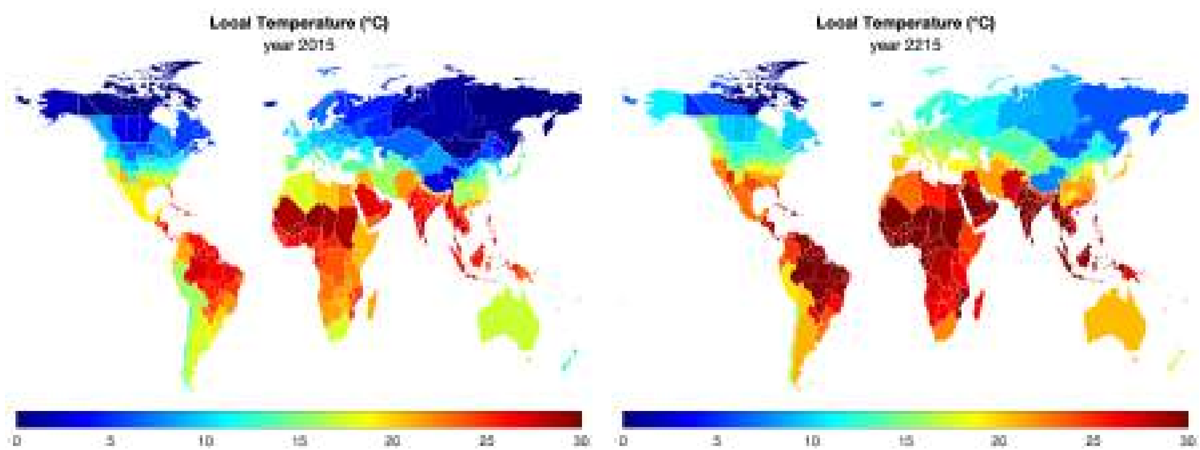

Figure 5: Local temperature in 2015 and 2215.

5.2 Welfare

To assess the welfare consequences of the gradual increase in temperature, I consider a factual scenario in which warming affects productivity, as described in Section 4.9, and a counterfactual scenario in which the aforementioned fundamentals are not distorted, so that climate productivity remains at its initial level.

Then, I define welfare losses in terms of the equivalent variation, $\mathcal{E}^{jr}$, which gauges the willingness to pay by workers in market jr in order to avoid global warming. Formally, the equivalent variation is defined as,

$$V_0'^{jr} = \log\left(B_0^{jr} u_0'^{jr}\right) + \beta V_1'^{jr} - \nu \log\left(\mu_0'^{(jr)(jr)}\right) = \sum_{t=0}^{\infty} \beta^t \log\left(\frac{B_t^{jr} c_t'^{jr}}{\left(\mu_t'^{(jr)(jr)}\right)^{\nu}}\right) = V_0^{jr} + \sum_{t=0}^{\infty} \beta^t \log(\mathcal{E}^{jr}),$$

$$\log(\mathcal{E}^{jr}) = (1-\beta)\sum_{t=0}^{\infty} \beta^t \log\left(\frac{c_t'^{jr}/c_t^{jr}}{\left(\mu_t'^{(jr)(jr)}/\mu_t^{(jr)(jr)}\right)^{\nu}}\right) = \sum_{t=1}^{\infty} \beta^t \log\left(\frac{\dot{u}_t'^{jr}/\dot{u}_t^{jr}}{\left(\dot{\mu}_t'^{(jr)(jr)}/\dot{\mu}_t^{(jr)(jr)}\right)^{\nu}}\right), \tag{36}$$

where the prime notation, x'_{t+1}, refers to the counterfactual scenario.[47] Henceforth, the welfare losses of a worker laboring in sector j and region r in the initial period are given by the present discounted value in real consumption and the option value, where the latter is summarized by the change in the fraction of workers that do not reallocate and the standard deviation of the taste shocks. When warming makes a market less suitable for residing and producing, the share of households that decide to stay in this region is expected to decrease. Hence, migration acts as a mitigation mechanism against global warming, attenuating the welfare losses.

To ease the exposition, define the hat notation, $\hat{x}_{t+1} = \dot{x}'_{t+1}/\dot{x}_{t+1}$, as the ratio of the counterfactual to the factual time differences. The change in real consumption is implicitly defined by,

$$\left(\hat{w}_{t+1}^{jr}\right)^{1-\varsigma} = \sum_{\tilde{j}=1}^{J} s_{t+1}^{(jr)(\tilde{j})} \left(\hat{s}_{t+1}^{(jr)(\tilde{j})}\right)^{-1} \left(\hat{p}_{t+1}^{\tilde{j}r}\right)^{1-\varsigma} \left(\hat{u}_{t+1}^{jr}\right)^{\vartheta^{\tilde{j}}}. \tag{37}$$

The change in real consumption does not only depend on the variations in wages and prices, but also on the variations in consumption shares. When warming rises the consumption share of the most affected goods, real consumption further declines. Hence, low income elasticity in agricultural goods relative to services acts as a magnification mechanism, aggravating welfare losses. Finally, the change in the price of goods depends on the change in trade openness, factor costs and fundamental productivity. Appendix B.4 further discusses the derivation of the equivalent variation.

Figure 6 displays, in its right panel, the density function of the welfare losses across different markets, where each observation is weighted by its population level. Positive values imply that workers are willing to pay a positive fraction of income to avoid the pernicious effects of this phenomenon. On average, the world is expected to undergo welfare losses of roughly one percent. However, there is a large degree of heterogeneity: the most affected markets are projected to experience losses of around 15%, whereas the most benefited markets might register welfare gains of more than 10%.

The left panel of Figure 6 illustrates the spatial distribution of average worker's equivalent variation.[48] In general, hot regions tend to be hurt, whereas cold regions tend to be benefited. However, the precise spatial distribution depends on the evolution of relative productivity across neighboring regions. Such features would be absent in a one-sector model.

Countries in the North of Africa, like Morocco, Algeria and Libya, experience small welfare losses or even welfare gains compared to their neighboring partners in Central Africa, which undergo larger welfare

[47] The last equality of equation (36) follows from the fact that in the initial period all variables are identical in the factual and counterfactual scenario, in particular, $u_0^{jr} = u_0'^{jr}$ and $\mu_0^{(jr)(jr)} = \mu_0'^{(jr)(jr)}$.

[48] The average workers' log-equivalent variation in a given region is defined as the weighted mean of log-equivalent variation across working sectors, where the weights are given by the employment shares.

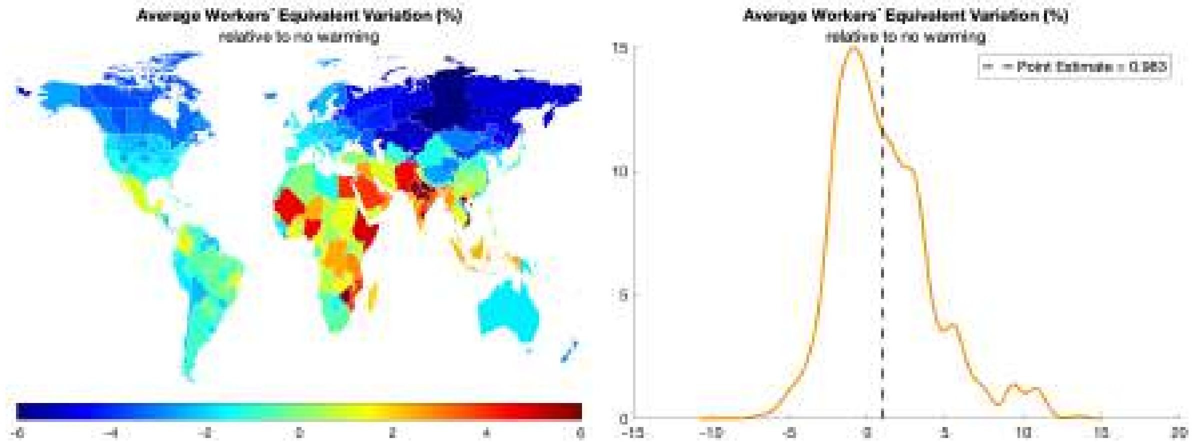

Figure 6: Average workers' welfare losses due to global warming.

damages. Since the former set of countries are relatively colder, they have a comparative advantage in producing agriculture goods, which represents up to 40% of the total value added in the initial period. Therefore, they harness in the comparative advantage to mitigate the damages experienced. A similar pattern is observed in the south of the continent.[49]

African countries in the Atlantic coast, like Liberia, Guinea and Senegal, tend to experience smaller welfare losses relative to their inland partners. Although these countries display similar levels of temperature in the initial period, the former warms slower than the latter. Less heterogeneity in welfare is observed in Europe and North America, as these regions display more uniform patterns of temperature and industrial composition. As for the within country differences, India concentrates the largest welfare losses in its northern provinces, since this area is mostly focused on the production of agricultural goods: around 40% of total value added. Whereas in the central and southern provinces, the production of agricultural goods accounts for roughly 20% of value added.

Within China, the coldest northern regions are projected to undergo welfare gains of roughly 5%. There is a stark distinction between mainland and coastal China: the former is mainly agrarian, whereas the latter is mainly devoted to services. Regarding the United States, the share of agriculture and construction is very small in the economy (less than 2% in terms of value added). Thus, the spatial dispersion of welfare damages is mostly driven by the trade and transportation sector, which accounts for roughly 25% of employment in the economy. This pattern highlights the relevance of a finer disaggregation within the service sector.

5.3 Labor Reallocation

The heterogeneity in productivity distortions induces a reallocation of workers across regions and economic sectors. Figure 7 compares the employment allocation in 2200 relative to the scenario with no warming. The right panel displays the global comparison across the six economic sectors. At the global level, warming induces almost 2% of workers to move into agriculture. Industry, construction, trade and transportation, and government and other services experience slight reductions in employment levels, of roughly half

[49] Likewise, Australia and New Zealand are colder compared to their neighboring partners in the Pacific Ocean. Thus, these two countries are able to lessen the welfare consequences of global warming.

percent. Financial services are projected to experience a decline in employment of almost 2.5%.

These results reflect the horserace between the production and consumption specialization discussed in Nath (2020). On the one hand, according to the patterns of comparative advantage, the declining agricultural productivity in the tropical regions would push resources, particularly labor, away from these areas. On the other hand, global warming is expected to make the world poorer, on average. Henceforth, lower income implies a larger consumption share for agricultural goods and, consequently, more resources are pulled into the more affected places to satisfy the larger demand. This shift in the consumption patterns is reinforced by the complementarity across goods. A higher consumption price in agricultural goods reduces the quantity demanded of this good. The low value for the elasticity of substitution induces a small quantity adjustment and thus the consumption patterns tilt towards the agricultural goods. On average, consumption specialization dominates production specialization.

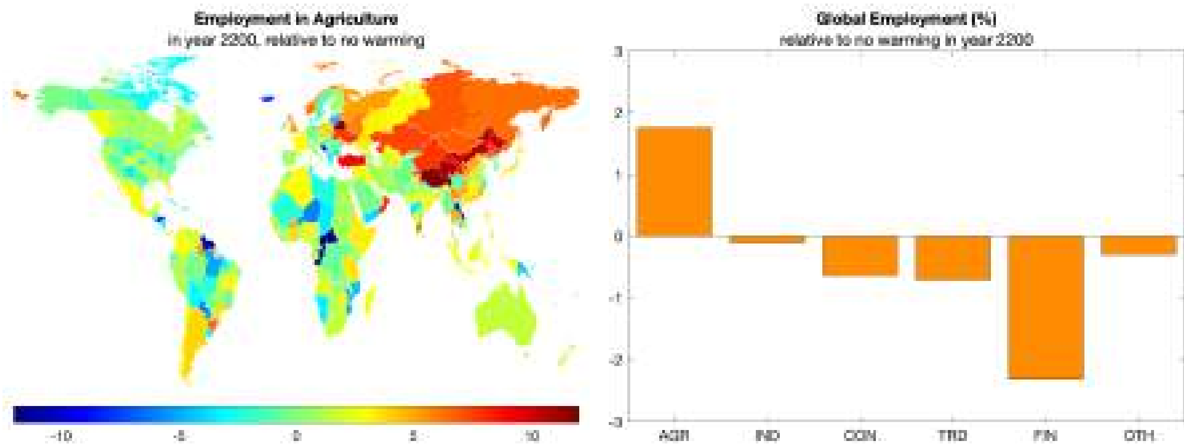

Figure 7: Labor reallocation in year 2200 due to global warming.

When evaluating the sectoral reallocation across spatial units, as illustrated in the left panel of Figure 7, the poorest regions are projected to experience increases in the number of agricultural workers. Such regions, like India and China, coincide with the warmest places, the ones projected to register large declines in income and thus the ones in which consumption specialization dominates production specialization. In the coldest and richest areas, like the United States, Canada and Europe, the opposite pattern is observed: income rises yield a larger consumption share in services and thus a lower demand for agricultural goods. Correspondingly, production specialization dominates consumption specialization.

Sector	Baseline
Agriculture	3.054
Industry	0.113
Construction	0.802
Trade and Transportation	0.405
Finance	-0.727
Government and Others	-0.294
Average	**0.983**

Table 5: Heterogeneous Welfare Losses across Working Sectors.

The reallocation of workers across economic sectors exemplifies the differentiated effects of global warming on workers, as presented in Table 5. On the one hand, workers in the agriculture sector are expected to undergo welfare losses three times larger than the average worker. Workers in industry, construction, and trade and transportation exhibit welfare losses smaller than one percent. On the other hand, workers in the finance and government and other services are projected to experience welfare gains of 0.7% and 0.3%, respectively. These results are explained by the fact that most service workers are concentrated in rich and cold countries, which benefit from the access to cheaper intermediate materials. Additionally, the decline in employment in these sectors augments the value added per worker by alleviating the congestion in the fixed factor.

6 Conclusions

This paper studies the heterogeneous effects of global warming across geographic locations and economic sectors, and their influence in shaping the labor reallocation and the distribution of welfare losses across markets. I develop a dynamic economic model with the patterns of structural transformation, an endogenous evolution of climate, and spatially distinct labor markets facing varying exposure to warming damages on productivity. The model explicitly recognizes the role of non-homothetic preferences, to reproduce the reallocation of economic activity across sectors when income grows, and trade of goods and migration of workers across regions and industries, to account for the costly ability of agents to adapt to this phenomenon.

To underscore the vast heterogeneity of the world at a high level of resolution, I consider 6 economic sectors and 287 regions, which comprise countries and subnational units in United States, Canada, Brazil, India, China, and Russia. To measure workers' mobility across regions and sectors, I collect data from a large set of international and national censuses and population surveys, and extend methodologies developed by the demographic literature to construct bilateral migration flows across more than 1,700 markets. To quantify the impact of temperature increases on productivity, I assemble a long panel of weather fluctuations and value added productivity, and exploit the temporal variation in a fixed effect econometric model to identify the non-linear effect of warming on productivity. Agriculture and construction stand out as the most climate sensitive sectors, so that an increase of local temperature of 1°C in the coldest countries of the world rises productivity by 3%. But in the hottest countries, productivity declines by roughly 6%.

The simulation of the model suggests a huge degree of heterogeneity in terms of welfare losses. On average, hot regions experience welfare losses, while cold places experience gains, but the exact spatial distribution hinges on the industrial composition. Such heterogeneity of warming impacts leads to a mobility response by workers. On aggregate, employment in agriculture rises, because the decline in average productivity reduces household's income, shifting the consumption patterns towards the agricultural subsistence good. Moreover, the employment distribution varies over space, so that the hottest and poorest countries of the world are the ones experiencing higher employment levels in agriculture. Consequently, agricultural workers face the greatest welfare losses: three times larger than the average worker.

The proposed model can be used as a workhorse model to study a number of additional dimensions of climate change. First, in order to have a more nuanced response of the spatial and industrial distribution of economic activity to warming damages, in which some economic clusters might flourish or vanish, this framework could be extended to incorporate an endogenous investment decision. Despite the challenges in modeling the capital accumulation of forward-looking agents in a dynamic spatial model, Kleinman et al. (2021) develop a tractable framework. Second, since global warming is a worldwide negative externality, policy might alleviate some of its negative impacts. Some of the most discussed tools in the policy debate are the use of carbon taxes and research subsidies to clean technology (Acemoglu et al., 2012, 2016). This framework could be enhanced to allow endogenous investments across energy sources and characterize the optimal market-specific tax on carbon dioxide emissions and subsidy on clean energy investment. Finally, global warming illustrates a particular dimension through which climate change might affect the economy. In addition, there are a number of climate shocks with a large regional component, like heat waves, droughts, storms, among others (Bakkensen and Barrage, 2019; Fried, 2019), affecting not only labor productivity, but also the available stock of physical capital. My research agenda pursues to evaluate the economic impacts of such extreme events.

Global warming presents a daunting challenge for humanity. A proper assessment of its consequences requires modern micro-founded economic models that incorporate multiple forms of adaptation and the rich spatial and industrial heterogeneity of the world. My hope is that this paper contributes to this effort.

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A Data

This Appendix delves into the description of the data and the construction of some variables.

A.1 Resolution

Aggregation of countries As for the country-level resolution, I mostly consider individual countries and group small countries or countries with few information into coarser geographical units. The aggregation of countries is the following: Albania and Macedonia; Austria and Liechtenstein; Belgium and Luxembourg; Benin and Togo; Denmark and Faore Islands; Spain and Gibraltar; Ethiopia, Eritrea, Djibouti and Somalia; France, Monaco and Andorra; Gabon, Equatorial Guinea and Sao Tome and Principe; Georgia and Armenia; Guinea and Guinea-Bissau; Guatemala and Belize; El Salvador and Honduras; Indonesia and Timor-Leste; Iraq, Kuwait and Syria; Italy, San Marino, Malta and Vatican; South Korea and North Korea; Morocco and Western Sahara; Madagascar and Seychelles; Mali and Mauritania; Mozambique, Mayotte and Comoros; Malaysia and Brunei; Nepal and Bhutan; Pakistan and Afghanistan; Romania and Moldova; Saudi Arabia and Bahrain; Sudan and South Sudan; Gambia and Senegal; Montenegro, Serbia and Kosovo; Libya and Tunisia; Burundi, Tanzania and Rwanda; Island of the Caribbean; Islands of Oceania; French Guiana, Guyana and Suriname; South Africa, Swaziland and Lesotho.

United States The 51 subnational units considered are: Alabama, Alaska, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin and Wyoming.

Canada The 13 subnational units considered are: Alberta, British Columbia, Manitoba, New Brunswick, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec, Saskatchewan, Northwest Territories, Nunavut and Yukon.[50]

China Taiwan is considered as an independent country. Due to lack of information, Macau and Hong Kong are considered as part of China. More precisely, as part of the province of Guangdong. Thus, the 33 subnational units considered are: Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Shandong, Shanghai, Shanxi, Sichuan, Tianjin, Xinjiang, Tibet, Yunnan and Zhejiang.

India The provinces of Dadra and Nagar Haveli and Daman and Diu are aggregated into Guajarat. The province of Lakshadweep is aggregated into Kerala. Andhra Pradesh and Telagana are considered as two different provinces, as they were officially separated in 2014. Thus, the 33 subnational units considered are: Andaman and Nicobar Islands, Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chandigarh, Chhattisgarh, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Karnataka,

[50] The first 10 subnational units are provinces and the las 3 are territories.

Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Puducherry, Punjab, Rajasthan, Sikkim, Tamil Nadu, Telangana, Tripura, Uttar Pradesh, Uttarakhand and West Bengal.

Brazil The 27 subnational units considered are: Acre, Alagoas, Amapá, Amazonas, Bahia, Ceará, Distrito Federal, Espírito Santo, Goiás, Maranhão, Mato Grosso, Mato Grosso do Sul, Minas Gerais, Pará, Paraíba, Paraná, Pernambuco, Piauí, Rio de Janeiro, Rio Grande do Norte, Rio Grande do Sul, Rondônia, Roraima, Santa Catarina, São Paulo, Sergipe and Tocantins.

Russia Russia is composed by 85 federal subjects. However, for convenience of governing and operation, 8 federal district were implemented. Table 6 reflects the correspondence between federal subjects and federal districts in Russia.

Federal District	Federal Subjects
Central	Belgorod Oblast, Bryansk Oblast, Vladimir Oblast, Voronezh Oblast, Ivanovo Oblast, Kaluga Oblast, Kostroma Oblast, Kursk Oblast, Lipetsk Oblast, Moscow Oblast, Oryol Oblast, Ryazan Oblast, Smolensk Oblast, Tambov Oblast, Tver Oblast, Tula Oblast, Yaroslavl Oblast and Moscow
Northwestern	Karelia Republic, Komi Republic, Arkhangelsk Oblast, Vologda Oblast, Kaliningrad Oblast, Leningrad Oblast, Murmansk Oblast, Novgorod Oblast, Pskov Oblast, Saint Petersburg and Nenets Autonomous Okrug
Southern	Adygea Republic, Kalmykia Republic, Krasnodar Krai, Astrakhan Oblast, Volgograd Oblast, Rostov Oblast Republic Crimea and Sevastopol
North Caucasus	Dagestan Republic, Ingushetia Republic, Kabardino-Balkar Republic, Karachay-Cherkess Republic, North Ossetia-Alania Republic, Chechen Republic and Stavropol Krai
Volga	Bashkortostan Republic, Mari El Republic, Mordovia Republic, Tatarstan Republic, Udmurt Republic, Chuvash Republic, Kirov Oblast, Nizhny Novgorod Oblast, Orenburg Oblast, Penza Oblast, Perm Krai, Samara Oblast, Saratov Oblast and Ulyanovsk Oblast
Ural	Kurgan Oblast, Sverdlovsk Oblast, Tyumen Oblast, Chelyabinsk Oblast, Khanty–Mansi Autonomous Okrug–Yugra and Yamalo-Nenets Autonomous Okrug
Siberian	Altai Republic, Tuva Republic, Khakassia Republic, Altai Krai, Krasnoyarsk Krai, Irkutsk Oblast, Kemerovo Oblast, Novosibirsk Oblast, Omsk Oblast and Tomsk Oblast
Far Eastern	Buryatia Republic, Sakha (Yakutia) Republic, Primorsky Krai, Khabarovsk Krai, Amur Oblast, Kamchatka Krai, Magadan Oblast, Sakhalin Oblast, Zabaykalsky Krai, Jewish Autonomous Oblast and Chukotka Autonomous Okrug

Table 6: Correspondence between federal subjects and federal districts in Russia.

A.2 Preferences

OECD Final Consumption Expenditure from Households This dataset is an unbalanced panel ranging from 1950 to 2018 comprising country-level data for 38 OECD and 22 non-OECD countries (Australia, Austria, Belgium, Brazil, Bulgaria, Cabo Verde, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, Germany, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Madagascar, Malta, Mexico, Morocco, Netherlands, New Zealand, North Macedonia, Norway, Peru, Poland, Portugal, Romania, Russia, Saudi Arabia, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States and Zambia), according to the COICOP classification, https://stats.oecd.org/Index.aspx?DataSetCode=SNA_TABLE5_ARCHIVE.

World Bank Global Consumption Database This dataset is a cross-section around the period 2000-2010, mostly focused on developing countries: it provides information for 90 countries (Afghanistan, Albania, Armenia, Azerbaijan, Bangladesh, Belarus, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Chad, China, Colombia, Congo Dem. Rep., Congo Rep., Cote d'Ivoire, Djibouti, Egypt, El Salvador, Ethiopia, Fiji, Gabon, Gambia, Ghana, Guatemala, Guinea, Honduras, India, Indonesia, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Lao PDR, Latvia, Lesotho, Liberia, Lithuania, Macedonia, Madagascar, Malawi, Maldives, Mali, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Peru, Philippines, Romania, Russia, Rwanda, Sao Tome and Principe, Senegal, Serbia, Sierra Leone, South Africa, Sri Lanka, Swaziland, Tajikistan, Tanzania, Thailand, Timor Leste, Togo, Turkey, Uganda, Ukraine, Vietnam, Yemen and Zambia) and subnational units for Brazil, India and South Africa, according to the COICOP classification. If consumption data for a country is present in the OECD and WB datasets, I prioritize the former given its larger horizon, https://datatopics.worldbank.org/consumption/AboutDatabase.

United States Consumption data for the United States is obtained from the Consumer Spending by State of the Bureau of Economic Analysis. This dataset displays information for the 50 states and the District of Columbia since 1997 according to the COICOP classification, https://www.bea.gov/data/consumer-spending/state.

Canada Consumption data for Canada is obtained from the Detailed household final consumption expenditure data, provincial and territorial of the Statistics of Canada. This dataset displays information for the 13 provinces and territories since 2000 in U.S. dollars according to the COICOP classification, https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3610022501.

China Consumption data for China is obtained from the People's Living Conditions of the Statistical Yearbook of Regional Economy. I obtain access to this dataset through the Princeton University Library. I define total consumption spending as the weighted sum of rural and urban consumption, where the weights are the population in rural and urban areas. This dataset displays information for the 33 provinces since 1999 in local currency according to the COICOP classification, https://library.princeton.edu/resource/40972.

Since some consumption goods in the COICOP classification are produced by more than one production sector in the ISIC classification, I consider the crosswalk displayed in Table 7, where each cell denotes the share of the consumption good produced by each sector. For each row, columns add up to one.

I compute the consumption expenditure of good $\tilde{\jmath}$ in sector j and in subnational unit r as the product of the consumption expenditure of good $\tilde{\jmath}$ in sector j and in country c times the share of consumption expenditure of good $\tilde{\jmath}$ in subnational unit r relative to the national consumption expenditure of good $\tilde{\jmath}$. Finally, Figures 8, 9 and 10 illustrate the spatial distribution of per capita consumption across the six economic sectors of interest.

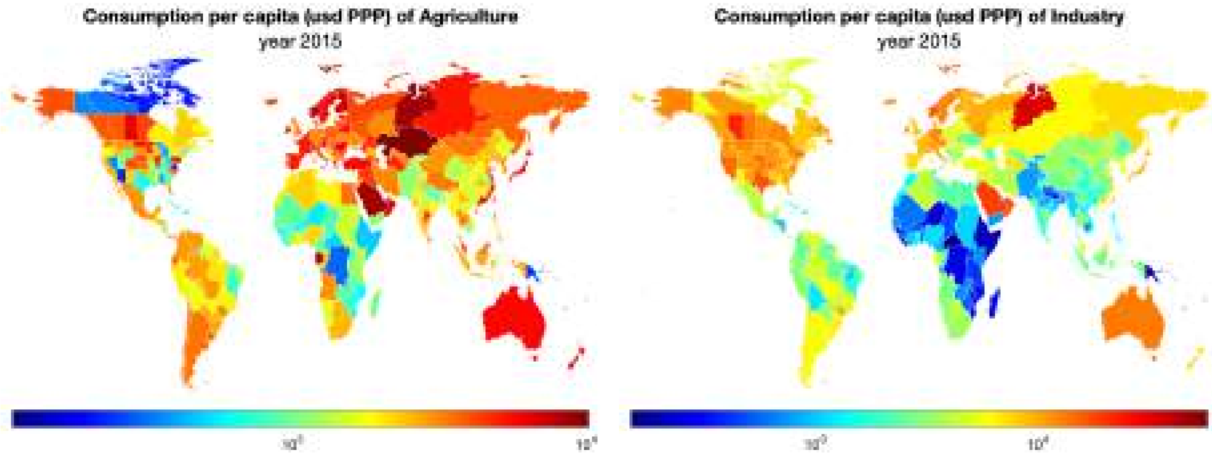

Figure 8: Consumption per capita in agriculture and industry in 2015.

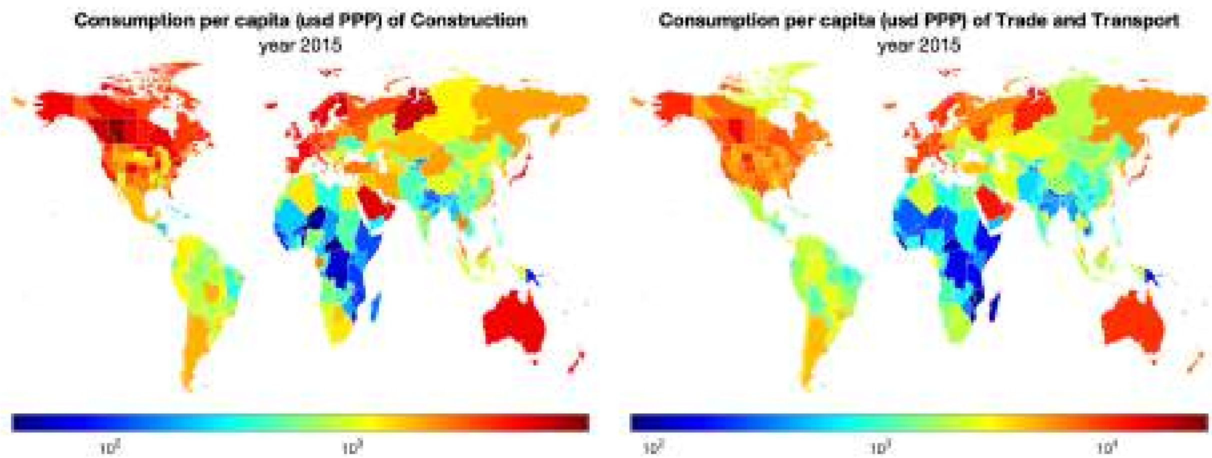

Figure 9: Consumption per capita in construction and trade and transport in 2015.

To input consumption data for the 21 countries and the 8 subnational units of Russia with missing information, I pose that consumption spending for each sector and region is a log-linear equation on region-level GDP per capita and population,

$$\log\left(p_t^{jr}c_t^{jr}\right) = \flat_0^j + \flat_1^j \log\left(GDPpc_t^r\right) + \flat_2^j \log\left(L_t^r\right) + \epsilon_t^{jr}. \tag{38}$$

Then, I employ the estimated coefficients to supplement the market specific consumption expenditure and construct the consumption shares. With data on the average consumption shares of good $\tilde{\jmath}$ in region r, $s_0^{\tilde{\jmath}r}$, I construct the consumption shares of good $\tilde{\jmath}$ of a worker laboring in market jr, $s_0^{(jr)(\tilde{\jmath})}$, by targeting the values predicted by the log-linear extrapolation, $\hat{s}_0^{(jr)(\tilde{\jmath})}$, on GDP per capita and population so that the

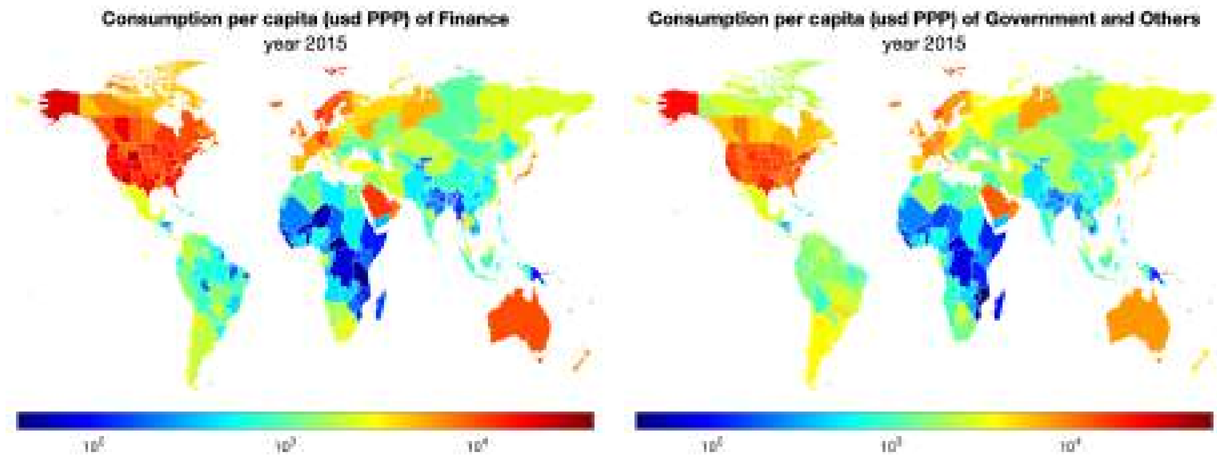

Figure 10: Consumption per capita in finance and government and others in 2015.

average value across economic sectors matches those observed in the data:

$$
\begin{aligned}
\min_{s} \quad & \sum_{j=1}^{J}\sum_{\tilde{\jmath}=1}^{J}\sum_{r=1}^{R}\left(s_0^{(jr)(\tilde{\jmath})}-\hat{s}_0^{(jr)(\tilde{\jmath})}\right)^2 \\
\text{st} \quad & \sum_{\tilde{\jmath}=1}^{J} s_0^{(jr)(\tilde{\jmath})} = 1 \\
& \sum_{j=1}^{J} s_0^{(jr)(\tilde{\jmath})} w_0^{jr} L_0^{jr} = s_0^{\tilde{\jmath}r} \sum_{j=1}^{J} w_0^{jr} L_0^{jr} \\
& s_0^{(jr)(\tilde{\jmath})} \in [0,1].
\end{aligned}
$$

A.3 Value Added and Employment

Penn World Table I obtain data on GDP and population for every country in the world from the Penn World Table version 10.0 (Feenstra et al., 2015). I employ this database, as it provides a consistent measure of value added across countries. More precisely, GDP is defined as the cumulative expenditure-side real GDP at chained PPP in U.S. dollars (`rgdpe`) from 2011 to 2015. Population levels (`pop`) are those of the year 2015, https://www.rug.nl/ggdc/productivity/pwt/?lang=en.

International Labor Organization (ILO) I disaggregate employment across working sectors by means of the annual employment by sex and economic activity database from the ILO, which displays information since 1991 for 276 countries in the world. I aggregate the employment of males and females for the year 2015 and compute the number of persons working in sector j in region r as the product of population from PWT times the share of employment in market jr relative to the total economy from the ILO, https://ilostat.ilo.org/data/.

Structural Change Database (SCD) I disaggregate value added across working sectors by means of the Structural Change Database (Szirmai and Foster-McGregor, 2017), which presents sectoral shares of GDP from 1950 to 2016 for 156 countries with than more than one million inhabitants, across nine economic sectors. I average the value added shares over the period 2011-2015 and compute value added in sector j in region r as the product of GDP from PWT times the share of GDP in market jr relative to the total economy from the SCD, https://www.merit.unu.edu/themes/3-economic-development-innovation-governance-and-institutions/structural-change-database-1950-2016/.

United States Value added and employment data across states for the United States are obtained from GDP by State and Employment by State from the Bureau of Economic Analysis, respectively. Information is displayed since 1997 according to the NAICS standard, https://www.bea.gov/data/gdp/gdp-state and https://www.bea.gov/data/employment/employment-by-state.

Canada Value added data across provinces and territories for Canada is obtained from the Gross domestic product (GDP) at basic prices, by industry, provinces and territories from the Statistics of Canada. This site displays information since 2001 according to the NAICS standard in chained 2012 U.S. dollars, https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3610040202.

Employment data is obtained from the 2016 Census of Canada.[51] Employed persons are those aged 15 years and over and usually relates to the establishment associated with the job the person held in the reference week. However, if the person did not work during that week but had worked at some time since January 1 of the prior year, the information relates to the job held longest during that period. Persons with two or more jobs were to report the information for the job at which they worked the most hours. Industrial classification follows the NAICS standard. In the Census, Northwest Territories, Nunavut and Yukon are aggregated as a single unit. I disaggregate them using population weights, https://gsg.uottawa.ca/data/teaching/soc/census16/user_guide.pdf.

China Value added and employment data across states for China are taken from the Macro Economy and Labor Statistics Yearbooks, respectively. I obtain access to this dataset through the Princeton University Library. As for value added, the dataset comprises nine sectors, which agriculture is defined as primary industry and trade and transportation as the sum of wholesale and retail, hotels and catering and transport, storage and post. As for employment, the dataset only comprises three sectors, primary industry comprises agriculture, secondary industry comprises industry and construction, and tertiary industry comprises trade and transportation, finance and government and other services. I disaggregate those sectors using the employment shares.

India Value added data across subnational units for India is taken from the States of India database, which presents information for agriculture; forestry and logging; fishing; mining and quarrying; manufacturing; electricity, gas and water supply; construction; trade, hotels, transport, storage, communication; financing, insurance, real estate and business services; and community, social and personal services. The first three sectors belong to agriculture and the next three to industry. I aggregate the provinces of Lakshadweep and Dadra and Nagar Haveli and Daman and Diu into larger provinces, as there is incomplete information for these units in this dataset.

Employment data across subnational units for India is taken from the Employment and Unemployment Surveys. These surveys are performed every two years, perform information for the 35 states of the country

[51] The Employment by industry, annual, provinces and economic regions from the Statistics of Canada displays incomplete information for the three territories of Canada.

and consider 21 economic sectors after 2010 and 17 economic sectors before 2010, https://data.gov.in/catalog/employment-and-unemployment-national-sample-survey?filters%5Bfield_catalog_reference%5D=87713&format=json&offset=0&limit=6&sort%5Bcreated%5D=desc.

Russia Value added and employment data across states for Russia are taken from the Federal State Statistics Service, which displays information at the federal district level according to the ISIC 3.1 classification, https://eng.rosstat.gov.ru/folder/11335.

Brazil Value added data across states for Brazil is taken from the Brazilian Institute of Geography and Statistics, which displays information since 2003 for 15 economic services: agriculture, industry (extraction industries; transformation industries; and electricity and gas), construction, trade and transportation (trade; transport, storage and communications; hotels and restaurants; and information and communication), finance (financial activities; real estate; and professional activities) and government and other services (public administration and defense; education and health; and other services), https://www.ibge.gov.br/en/home-eng.html.

Employment data across states for Brazil is taken from the National Household Sample Survey Microdata. The mapping between the main activity codes in the survey and the six economic sectors of interest are: agriculture (11-50), industry (100-410), construction (450), trade and transportation (500-640), finance (650-740) and government and other services (750-998). Access to the information on `Stata` comes from the package `datazoom_pnad` developed by PUC-Rio, https://www.ibge.gov.br/en/statistics/social/education/20620-summary-of-indicators-pnad2.html?=&t=o-que-e.

I compute the number of persons working in sector j in subnational unit r as the product of the number of persons working in sector j in country c times the share of workers residing in working in sector j in subnational unit r relative to the national number of workers in sector j. Finally, Figures 11, 12 and 13 illustrate the spatial distribution of per capita consumption across the six economic sectors of interest.

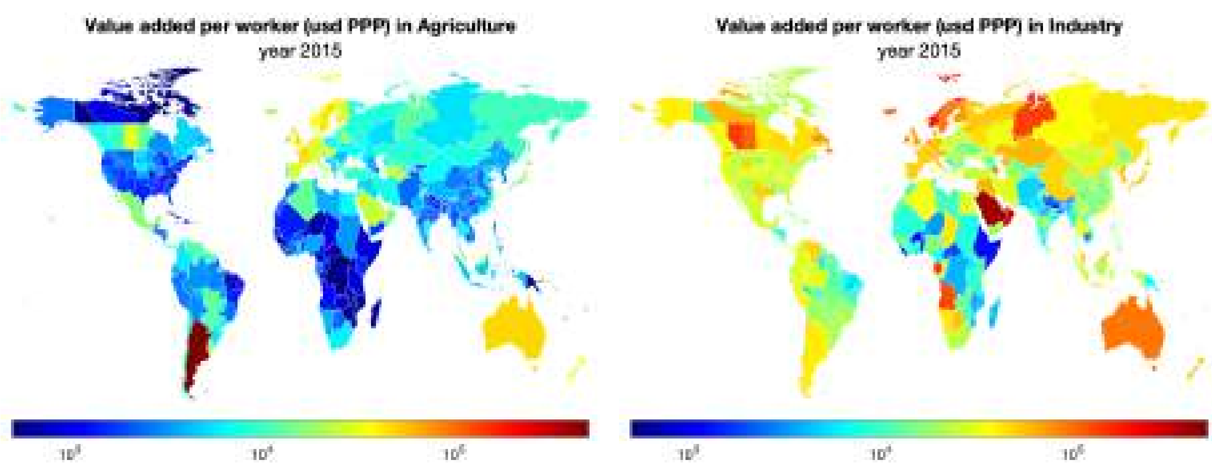

Figure 11: Value added per worker in agriculture and industry in 2015.

To estimate the share of value added in gross production, I target the global values observed in the EORA database, subject to the feasibility constraint, given by the sum across economic sectors of equation

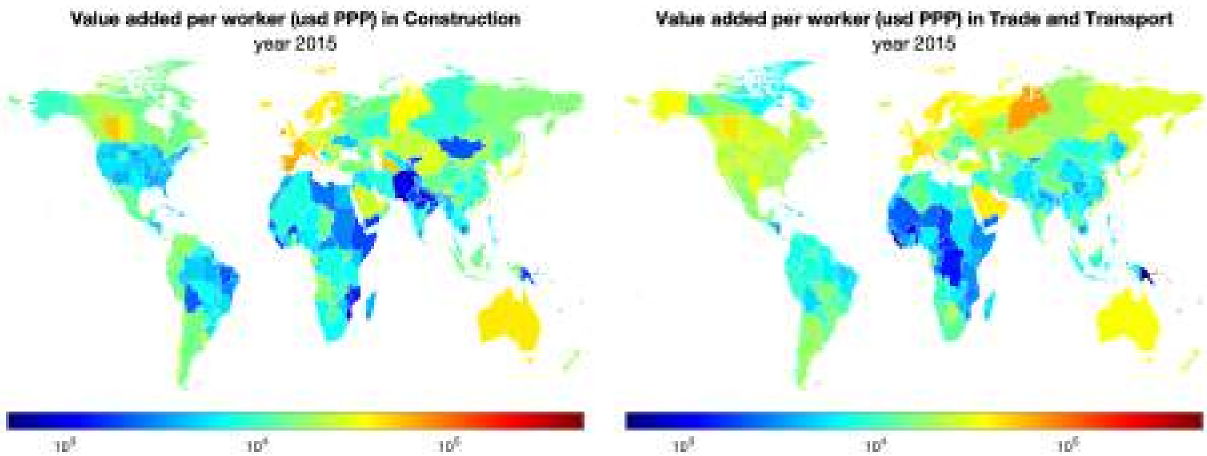

Figure 12: Value added per worker in construction and trade and transport in 2015.

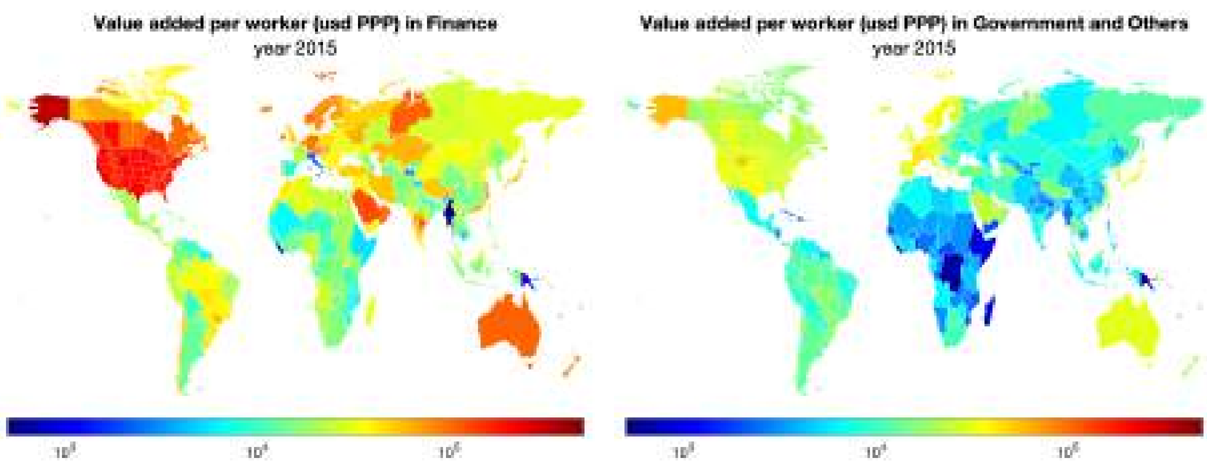

Figure 13: Value added per worker in finance and government and others in 2015.

(20), as shown below:

$$
\begin{aligned}
\min_{\mho} \quad & \sum_{j=1}^{J}\sum_{r=1}^{R}\left(\mho^{jr}-\hat{\mho}^{j}\right)^{2} \\
\text{st} \quad & \sum_{j=1}^{J}(\mho^{jr}-1)VA_0^{jr} = \sum_{j=1}^{J}X_0^{jr} - \sum_{j=1}^{J}(1-\alpha^{E})VA_0^{jr} \\
& (\mho^{jr}-\alpha^{E})VA_0^{jr}L_0^{jr} = \sum_{\tilde{r}=1}^{R}\pi_0^{(jr)(j\tilde{r})}X_0^{j\tilde{r}} \\
& \mho^{jr} \geq 1,
\end{aligned}
$$

where $\mho^{jr} = 1/(1-\omega^{jr})$ denotes a transformation of the share of value added in gross production, $\hat{\mho}^{j}$ the global average value observed in the EORA database and VA_t^{jr} the value added observed in the data. To estimate the share of materials in non-value added, I target the input output linkages observed in the EORA database, $\hat{\omega}^{(jr)(\tilde{\jmath}r)}$, subject to the feasibility constraint (20):

$$\begin{aligned}
\min_{\omega} \quad & \sum_{j=1}^{J}\sum_{\tilde{\jmath}=1}^{J}\sum_{r=1}^{R}\left(\omega^{(jr)(\tilde{\jmath}r)} - \hat{\omega}^{(jr)(\tilde{\jmath}r)}\right)^2 \\
\text{st} \quad & \sum_{\tilde{\jmath}=1}^{J}\omega^{(jr)(\tilde{\jmath}r)}(\mho^{\tilde{\jmath}r}-1)VA_0^{\tilde{\jmath}r} = X_0^{jr} - s_0^{jr}\sum_{\tilde{\jmath}=1}^{J}(1-\alpha^E)VA_0^{\tilde{\jmath}r} \\
& \sum_{j=1}^{J}\omega^{(jr)(\tilde{\jmath}r)} = 1 \\
& \omega^{(jr)(\tilde{\jmath}r)} \in [0,1].
\end{aligned}$$

A.4 Trade Flows

EORA Database The EORA Database is a cross-section of national input output tables and bilateral trade information across 187 countries and 26 sectors from 1990 to 2015. The mapping between this industrial classification and the six economic sectors of interest is displayed in Table 8.[52] It presents data for goods and services sectors, but does not display a subnational disaggregation. I use information for the period 2011-2015.

U.S. Census Bureau I employ the USA Trade Online, `https://usatrade.census.gov`, to obtain data on state exports and imports relative to all countries in the world at a monthly frequency since 2002. Data for agriculture (111-114), mining (211-212) and manufacturing (311-339) is presented according to the North American Industry Classification (NAICS) classifications.

Commodity Flow Survey The Commodity Flow Survey (CFS) captures data on shipment originating from business establishments in the mining, manufacturing and wholesale and retail trade industries located in the 50 states and the District of Columbia. The establishments are asked to provide shipment information once in each quarter. The CFS is performed every five year and I use the information for the year 2012.

Trade Data Online, Statistics Canada The Trade Data Online from the Statistics of Canada displays information on exports and imports between each province in Canada and each country in the world and each state in the United States since 2002. Data for agriculture (111-115), mining (211-213), utilities (221) and manufacturing (311-339) is presented according to the NAICS classifications.

China Customs The China Customs data is obtained from the EPS China Statistics, which presents data on exports and imports at a quarterly frequency from 2012 to 2017. I obtain access to this dataset through the Princeton University Library. Trade flows between each province in China and each country in the world are displayed for agriculture (01-05), mining (06-12) and manufacturing (13-43), according to the Industrial Classification for National Economic Activities (CSIC) Revision 2011 classification.[53]

[52] In the quantification of the model, I exclude the sector Re-Export and Re-Import.

[53] Data from 2009 to 2011 is displayed according to the CSIC Revision 2002 classification.

Brazilian International Trade Statistics The Brazilian foreign trade statistics, http://comexstat.mdic.gov.br/en/home, displays information on exports and imports at a monthly frequency since 1997 between each state in Brazil and each country in the world, according to the ISIC classification.

A.5 Migration Stocks and Demographic Data

United Nations UN displays estimates of the number of international migrants disaggregated by place of birth, across 232 countries. Data comes from national statistics and mostly from population censuses. The estimates are presented for every five years from 1990 to 2020, https://population.un.org/unmigration/index_sql.aspx.

The Population Division of the United Nations also displays information on country-level births and deaths, https://population.un.org/wpp/.

World Bank Global matrices of bilateral migration stocks spanning the period 1960-2000, at a decade frequency, disaggregated by gender and based primarily on the foreign-born concept are presented. Data is constructed from hundreds of censuses and population registers.

United States I employ the one year American Community Survey for the years 2015, 2010, 2005 and 2000 and 5% state sample for 1990. The migration stock for 1995 is estimated as the average between 1990 and 2000. I consider all individuals, regardless of their age, sex or socioeconomic conditions.

For each year, I observe information by place of residence for each of the 50 states and the District of Columbia. As for place of birth, the information presented for some countries tends to be scattered across years. To circumvent this issue, I aggregate countries of birth into 21 coarser regions to have a consistent path over time. More precisely, I use the relationship displayed in Table 9.

Information for state-level births and deaths are obtained from the National Vital Statistics System of the National Center for Health Statistics, https://www.cdc.gov/nchs/data_access/ftp_data.htm.

Canada I employ the Census Public Use Microdata File on Individuals for the years 2016, 2006, 2001, 1996 and 1991 and the National Household Survey Public Use Microdata File on Individuals for the year 2011, representing 2.7% of the Canadian population. Information was collected from the Statistics Canada Electronic File Transfer Service.

Information for province-level births and deaths are obtained from the Canadian Vital Statistics of the Statistics of Canada, https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&Id=1181459&dis=1 and https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=3233.

China I employ the Census of China for the years 2010, 2000 and 1990 and the Population Sampley Surveys for the years 2015, 2005 and 1995. I obtain access to this dataset through the Princeton University Library. Information is disaggregated by province or city of residence, province of registration and sex.

Information for province-level births and deaths are obtained from the Macro Economy Statistical Yearbook of China. I obtain access to this dataset through the Princeton University Library.

India I employ the Census of India for the years 2011, 2001 and 1991.

Information for state-level births and deaths are obtained from the Government of India, Ministry of Statistics, https://data.gov.in/catalog/crude-birth-rate-india?filters%5Bfield_catalog_reference%5D=86930&format=json&offset=0&limit=6&sort%5Bcreated%5D=desc and https://data.gov.in/catalog/health-and-family-welfare-statistics-2019-20?filters%5Bfield_catalog_reference%5D=6846674&format=json&offset=0&limit=6&sort%5Bcreated%5D=desc.

Russia I employ the Census of India for the years 2010 and 2002.

Brazil I employ Brazil National Household Sample Survey and access the information on Stata using the package datazoom_pnad developed by PUC-Rio.[54]

Information for state-level births and deaths are obtained from the System of Vital Statistics of the Brazilian Institute of Geography and Statistics, https://www.ibge.gov.br/en/statistics/social/population/16835-vital-statistics.html?=&t=o-que-e.

A.6 Energy

Emissions Database for Global Atmospheric Research (EDGAR) I employ the EDGAR v6.0 GHG database, which provides information on the three main greenhouse gases (e.g., carbon dioxide, methane and nitrous oxide) for almost 200 countries since 1971,[55] https://edgar.jrc.ec.europa.eu/dataset_ghg60.

IEA International Aviation and Shipping I obtain the disaggregation of International Aviation and Shipping carbon dioxide emissions across 143 countries and 3 regions since 1971 from the IEA's CO_2 Emissions from Fuel Combustion. Regions are disaggregated across countries using the CO_2 shares derived from EDGAR.

British Petroleum I employ the Statistical Review of World Energy to obtain information on clean energy by source (nuclear energy, hydroelectricity and renewables) since 1971 for 79 countries and 12 regions. I decompose regions into countries following the same proportions as in the use of fossil fuels. To make comparable CO_2 emissions and use of clean energy, I take the ratio of tons of carbon dioxide to tons of oil equivalent to be 2.8466, https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html.

IEA Extended World Energy Balances I decompose the total energy use in each spatial unit across economic sectors, employing the IEA Extended World Energy Balances. This table contains an extended set of data on the energy consumption of different energy sources across across diverse final uses. More precisely, I compute the global use of energy and construct the share of energy used across sectors according

[54] See http://www.econ.puc-rio.br/datazoom/english/pnad.html.

[55] I employ this database, rather than information from British Petroleum, as the former displays a finer country-level disaggregation.

to the final consumption.[56] Finally, due to the lack of disaggregation for some countries and subnational units, I use the global shares to decompose the energy use across all regions, https://www.oecd-ilibrary.org/energy/data/iea-world-energy-statistics-and-balances/extended-world-energy-balances_data-00513-en.

United States I employ the State Energy Data System of the U.S. Energy Information Administration, which displays yearly information since 1960. Energy sources are defined as coal, natural gas, petroleum, nuclear and total renewable energy. The first three are fossil fuels and the last two are clean energy, https://www.eia.gov/totalenergy/data/annual/.

Canada As for fossil fuel use, I employ the Canada's Official National Greenhouse Gas Inventory to construct carbon dioxide emissions across provinces and territories. Data is provided since 1990 and it allows a decomposition by economic sector, https://open.canada.ca/data/en/dataset/779c7bcf-4982-47eb-af1b-a33618a05e5b.

As for clean energy use, I employ the electric power generation by type of electricity from the Statistics of Canada. More specifically, hydraulic, nuclear, solar, tidal and wind are considered as clean energy sources, https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=2510001501.

China I employ the China Energy Statistical Yearbook to compute subnational energy production data. I obtain access to this dataset through the Princeton University Library. As for fossil fuels, I consider information on physical units of crude oil and coal production.[57] As for clean energy, I consider information on hydro and thermal power generation, both presented in kilowatt per hour.

India As for fossil fuels, I employ the GHG Platform – India to obtain information on state-level CO_2 emissions since 2005. The database, http://www.ghgplatform-india.org, allows a decomposition across economic sectors. As for clean energy, I employ the same subnational decomposition as in fossil fuels.

Brazil As for fossil fuels, I employ the Greenhouse Gases Emission and Removal Emission System (SEEG), http://seeg.eco.br/download, which provides data since 1990 across economic sectors and municipalities. As for clean energy, I employ the same subnational decomposition as in fossil fuels.

Russia I employ information from Xiao et al. (2021), which provides information on energy use of Russia's 80 constituent units from 2010 to 2017 across economic sectors. The 80 constituent units are then gathered into 8 federal subjects. As for fossil fuels, I consider the sum of crude oil, natural gas, oil, coal and combustible indirect energy resources. As for clean energy, I consider thermal energy.

[56]Commercial and public services are allocated to utilities and services. Residential use is omitted in the disaggregation, as it cannot be identified to a particular sector. I extend the definition of final consumption and allocate the transformation processes and energy industry own use to the industry sector.

[57]For energy sources to be in the same units, I follow Golosov et al. (2014) and consider that one ton of oil and one ton of oil generate 0.846 tons and 0.716 tons of carbon dioxide, respectively.

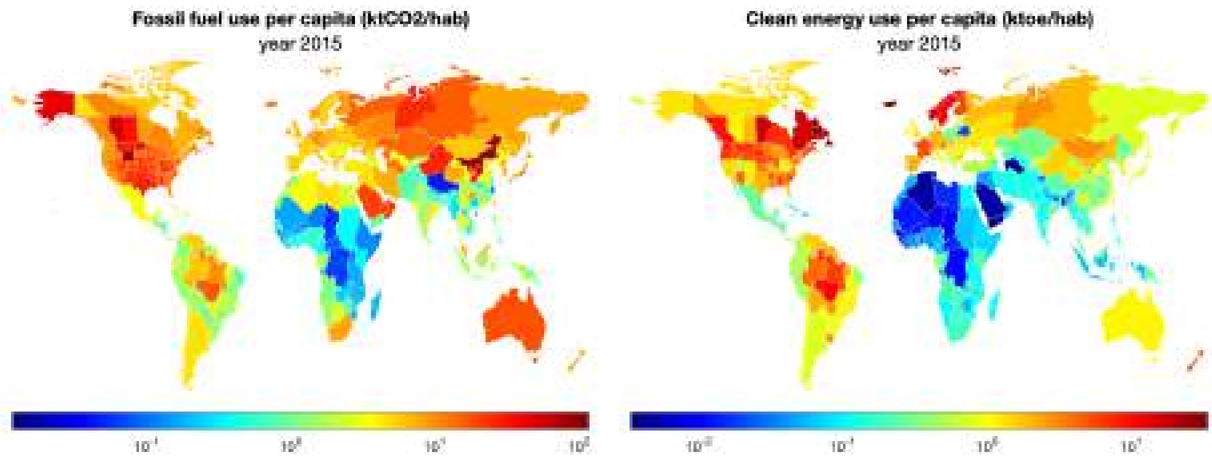

Figure 14: Fossil fuel and clean energy use per capita in 2015.

Extraction Cost Function Following Cruz and Rossi-Hansberg (2021), I specify the extraction cost as the following increasing and convex function,

$$h(\Upsilon_t) = \left(\frac{h_1}{h_2 + \exp\left(-h_3\left(\Upsilon_t - h_4\right)\right)}\right) + \left(\frac{h_5}{h_6 - \Upsilon_t}\right)^3,$$

where h_6 denotes the total reserves of carbon in the ground. The value of this parameter is set to the cumulative flow of CO_2 for the next five centuries according to in the RCP 8.5 scenario of the IPCC (2013), that is, $19,500$ $GtCO_2$. The remaining parameters target the extraction cost presented in Bauer et al. (2017).

A.7 Weather

I employ weather data from Matsuura and Willmott (2018), who provide gridded monthly data on temperature and precipitation since 1900 to 2017 at a resolution of $0.5° \times 0.5°$. To identify cells to countries, I consider that each cell corresponds a single country: the one with most territory in it. Few exceptions are performed for very small units, which otherwise would have no representation in the grid. I consider that the weather variables of Hong Kong, Singapore, Malta, Bahrain and District of Columbia correspond to that of the cell centered at $(22.75, 114.25)$, $(1.75, 103.75)$, $(36.75, 14.75)$, $(1.75, 103.75)$ and $(38.75, -77.25)$, respectively. Then, I aggregate gridded weather data at the region-level, employing population weights. Gridded population for the year 2000 is obtained from the Gridded Population of the World version 4 (Doxsey-Whitfield et al., 2015).[58]

A.8 Damage Function

This subsection describes the data sources employed in the identification of the damage function of temperature on productivity, as well as some robustness exercises.

[58] Alternatively, I could have aggregated cells into countries using crop or pasture weights from Ramankutty et al. (2008). In order to have a consistent measure across economic sectors, I prefer the population weights.

A.8.1 Value Added and Employment

Real value added, expressed in local currency, and employment, measured in number of persons, are mainly taken from the GGDC 10-sector (Timmer et al., 2015a) and the OECD STAN database (OECD, 2020). The former database provides information for 42 countries, mainly from Africa, Asia and Latin America; whereas the latter for 37 countries, mainly from North America, Europe and Oceania. To enlarge the spatial coverage, I supplement these datasets with continent-specific information, namely EU KLEMS database (O'Mahony and Timmer, 2009), Expanded Africa Sector Database (Buadi and Szirmai, 2018) and Asian Productivity Organization database (APO, 2020). I transform monetary units into U.S. dollars, using the purchasing power parities of the PWT dataset (Feenstra et al., 2015).

Since the spatial patterns of productivity and temperature might be quite heterogeneous within large countries, I disaggregate the United States into its 50 states and the District of Columbia, as in Colacito et al. (2019). Data on sectoral value added at the subnational level comes from the Bureau of Economic Analysis: from 1997 to 2020, the sectoral classification follows the North American Industry Classification System and from 1977 to 1997 follows the Standard Industrial Classification. I employ the former period of time as baseline and extrapolate to the past using the growth rates of the latter period of time. Since employment at the sector-state level from the BEA comprise a narrow span of time (1990-2017), I construct this measure using the Current Population Survey, which is the primary source of labor force statistics for the population of the United States and provides data since 1962.

Table 10 illustrates the sectors considered, as well as their correspondence across different industrial classifications, namely ISIC 3.1, ISIC 4.0, NAICS and SIC. Table 11 displays the countries and subnational units considered in the analysis. When one country is present in more than one dataset, I prioritize the information as follows: Expanded Africa Sector, GGDC 10-sector, OECD STAN, EU KLEMS, Expanded Africa Sector and Asian Productivity Organization.[59] Below, I describe in more detail the datasets employed.

GGDC 10-sector The GGDC 10-Sector Database provides a long-run internationally comparable dataset on sectoral productivity performance for 42 countries from Africa, Asia, and Latin America. Variables covered in the data set are annual series of value added, output deflators, and persons employed for 10 broad sectors, according to the industrial classification ISIC 3.1, `https://www.rug.nl/ggdc/structuralchange/previous-sector-database/10-sector-2014?lang=en`.

OECD STAN The STAN database includes annual measures of output, value added and its components, labor input, investment and capital stock, from 1970 onward. The latest version of the STAN Database employs the industrial classification ISIC 4.0. This database comprise information for 37 countries, mainly from North America, Europe and Oceania, `https://www.oecd.org/sti/ind/stanstructuralanalysisdatabase.htm`.

EU KLEMS EU KLEMS comprise information for all individual EU-28 countries and United States. I employ the basic files, which contain information on value added and employment. The sectoral classification follows ISIC 4.0, `http://www.euklems.net`.

[59] This decision is based on the length of the time dimension of these datasets.

Expanded Africa Sector The Expanded Africa Sector Database presents data on value added at current prices, value added at constant prices, price deflators and employment for 10 sectors of the economy, according to the industrial classification ISIC 3.1, in 18 African economies, from 1960 until 2015, https://www.merit.unu.edu/themes/3-economic-development-innovation-governance-and-institutions/expanded-africa-sector-database-easd-1960-2015/.

Asian Productivity Organization The APO Productivity Database provides information on employment and value added by industry at current and constant prices. The industry classification follows ISIC 3.1, https://www.apo-tokyo.org.

Bureau of Economic Analysis The Department of Commerce's BEA displays annual data on value added by industry and state from 1963 to 2017.[60] Industry data from 1963 to 1997 are categorized using the SIC codes, while data from 1997 to 2011 follow NAICS. I employ the former period of time as baseline and extrapolate to the past using the growth rates of the latter period of time.

Current Population Survey Since employment at the sector-state level from the BEA comprise a narrow span of time (1990-2017), I construct this measure using the Current Population Survey, which allows me to construct a panel data from 1962 to 2017. More precisely, I consider all persons aged 15 or more, who were currently employed or had previously worked during the current year and were looking for work. I employ the industrial classification of the 1990 Census Bureau industrial classification system.

A.8.2 Capital

Using capital stocks to evaluate the contribution of capital is likely to be misleading, since long-lived assets, like structures, get a very high weight compared to short-lived assets, like software. Capital services are constructed based on capital stocks, which are computed through the perpetual inventory method, as in Inklaar et al. (2019) and Edquist and Henrekson (2017).

Investment data at the country-level in current and constant prices is taken from the Capital Details of PWT. Such database considers four types of assets: residential and non-residential structures, machinery and equipment, transport equipment, and others.

As for investment data at the subnational-level in the United States, I follow Garofalo and Yamarik (2002) consider that the state-level investment price is the same in the whole country and that the state-level share of nominal investment equals the share of nominal value added.

To initialize the perpetual inventory method, I compute the initial value of the nominal capital stock, for

[60] Data from 1957 to 1962 can be obtained from the U.S Census Bureau Bicentennial Edition.

each asset a and sector j and region r, as an asset-specific constant fraction κ^a of the nominal value added,[61]

$$P_0^{I,a,r} K_0^{a,j,r} = \kappa^a P_0^{VA,j,r} VA_0^{j,r}, \qquad \kappa^a = \begin{cases} 2.2, & a = \text{Structures} \\ 0.3, & a = \text{Machinery} \\ 0.1, & a = \text{Equipment} \\ 0, & a = \text{Others} \end{cases},$$

where the values for κ^a are taken from Table 4 of Inklaar and Timmer (2013). The real capital stock accumulates due to investment and the non-depreciated part of the previous capital. Investment at the asset-sector level is constructed as the asset-level investment observed in the data times the sectoral share of value added.[62] The depreciation rate, δ^a, is asset-specific to account for the fact that software depreciates faster than structures,

$$K_{t+1}^{a,j,r} = \left(\frac{VA_t^{j,r}}{VA_t^r}\right) I_t^{a,r} + (1-\delta^a) K_t^{a,j,r}, \qquad \delta^a = \begin{cases} 0.02, & a = \text{Structures} \\ 0.148, & a = \text{Machinery} \\ 0.189, & a = \text{Equipment} \\ 0.212, & a = \text{Others} \end{cases},$$

where the values for this parameter are taken from Table 2 of Inklaar and Timmer (2013). Based on the capital stocks and the asset- and country-specific investment prices, $p^{I,a,r}$, provided by the Capital Details of PWT, I compute the internal rate of return, $irr_t^{j,r}$, for each sector and region:

$$irr_t^{j,r} = \frac{\alpha^H GDP_t^r - \sum_{a=1}^A P_t^{I,a,r} \delta^a K_t^{a,j,r} + \sum_{a=1}^A \left(P_t^{I,a,r} - P_{t-1}^{I,a,r}\right) K_t^{a,j,r}}{\sum_{a=1}^A P_{t-1}^{I,a,r} K_t^{a,j,r}}.$$

The first term, $\alpha^H GDP_t^r$, denotes the the overall capital compensation in the economy, defined as the share α^H of Gross Domestic Product. The internal rate of return varies across industries, but not across assets, as it is equalized across assets in a competitive market. The internal rate of return is then used to derive the rental prices, $q_t^{a,j,r}$. The rental price equals the price at which the investor in indifferent between buying and renting the capital good:

$$q_t^{a,j,r} = P_{t-1}^{I,a,r} irr_t^{j,r} + P_t^{I,a,r} \delta^a - \left(P_t^{I,a,r} - P_{t-1}^{I,a,r}\right).$$

Finally, the change in capital services in industry j and region r can be obtained as shown below, where the weight $\tilde{v}_t^{a,j}$ is the two-period average share of compensation by each type of capital in the total value of capital compensation for all industries.[63] The initial level of capital services is the nominal value of the

[61] Alternatively, I could have used the steady-state relationship from the Solow growth model, $K_0^{a,j} = I^{a,j}/(g^a + \delta^a)$, where $I^{a,j}$ is the steady-state value of investment, g^a is the growth rate of investment and δ^a is the depreciation rate. However, Inklaar and Timmer (2013) argue that a linear relation between capital and output provides superior results.

[62] OECD provides investment data across countries, economic sectors and assets. Nevertheless, its limited geographical scope precludes its use in this setting.

[63] To derive capital stocks, replace $q_t^{a,j,r} K_t^{a,j,r}$ with $P_t^{I,a,r} K_t^{a,j,r}$ in the expression for $v_t^{a,j,r}$.

capital stock across assets for a given sector and region,

$$\Delta \log \left(K_t^{j,r} \right) = \sum_{a=1}^{A} \tilde{v}_t^{a,j,r} \Delta \log \left(K_t^{a,j,r} \right),$$
$$\tilde{v}_t^{a,j,r} = 0.5 \left(v_t^{a,j,r} + v_{t-1}^{a,j,r} \right),$$
$$v_t^{a,j,r} = \frac{q_t^{a,j,r} K_t^{a,j,r}}{\sum_{a=1}^{A} q_t^{a,j,r} K_t^{a,j,r}}$$

A.8.3 Trade

Trade data comes from the Trade Details of PWT (Feenstra et al., 2015). More precisely, agricultural trade flows correspond to food and beverages and manufacturing trade flows correspond to industrial supplies, fuels and lubricants, capital goods, transport equipment and consumer goods. The remaining sectors are considered as non-tradable.

A.8.4 Robustness

The main specification evaluating the impact of temperature on productivity, given by equation (34), considers that the error term is clustered by country and year-continent. Table 12 defines continents, as in Dell et al. (2012).

Tables 13 and 14 consider a finer disaggregation of the sectoral composition. Specifically, I decompose industry into mining, manufacturing and utilities, and separate trade and transportation, and government and other services. Within the industry sector, manufacturing displays significant warming effects, in order of magnitude similar to those of trade and transportation.

Figure 15 displays, in its left panel, the point estimates of the damage function of precipitation on productivity for the agriculture sector, its 90%, 95% and 99% confidence intervals, and the effect for a selected number of countries, namely, Egypt (EGY), China (CHN), United States (USA), India (IND), Brazil (BRA), Myanmar (MMR), Costa Rica (CRI), Fiji (FJI), and Bhutan (BTN). In its right panel, Figure 15 shows the spatial pattern of precipitation in 2015, measured in log mm. Relative to temperature, the impacts of precipitation are one order of magnitude lower in this sector.

The baseline specification, given by equation (34), imposes that the marginal damage function of weather on productivity is specific for each sector, through the coefficients $(\tau_1^j, \tau_2^j, \rho_1^j, \rho_2^j)$, and country, through the level of temperature. In this sense, such specification abstracts away from the potential adaptation mechanisms that might occur at the cross-country level. For instance, richer countries might be better suited to attenuate the warming effects on productivity relative to poor countries. Analogously, historically hot countries might be better suited to deal with temperature increases relative to temperate or cold countries.

Tables 15 an 16 test the sensitivity of the empirical results in agriculture to the covariates considered. Regarding Table 15, column (1) displays the baseline results. Column (2) augments the set of covariates to include an interaction between weather variables and the 30-year rolling average of income. Column (3) adds the interaction between weather variables and the 30-year rolling average of temperature. Column (4) considers that not only current temperature affects productivity, but also the temperature of the previous year. All the interactions and additional covariates display non significant results. Column (5) performs a placebo experiment to test whether current productivity reacts to changes of one-year-ahead temperature. Those coefficients are non significant.

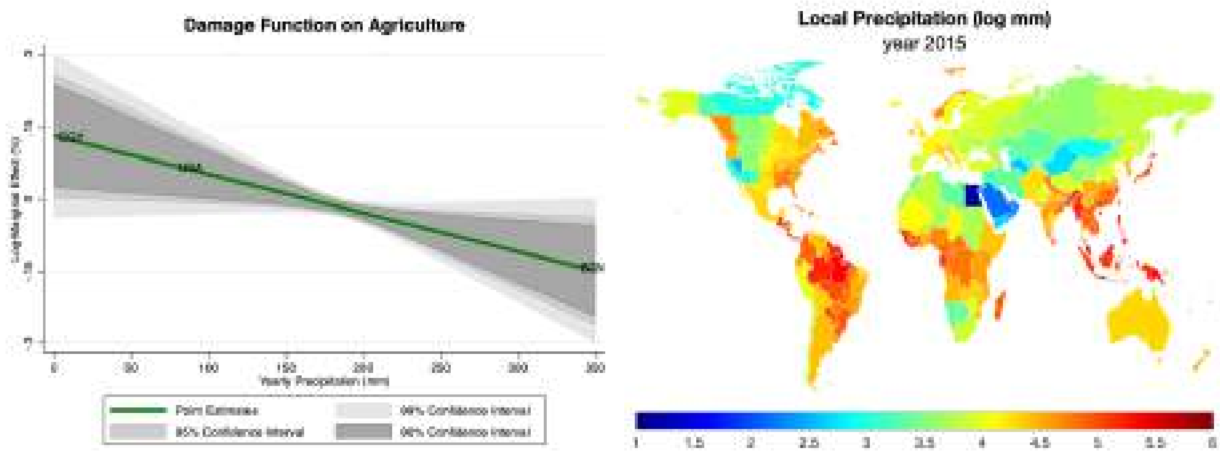

Figure 15: Damage function of precipitation on agriculture and spatial pattern of precipitation in 2015.

Regarding Table 16, column (2) interacts the level of temperature with the 30-year rolling average of the temperature range, defined as the difference between the maximum and minimum yearly temperature. Columns (3) and (4) incorporate the interaction between weather variables and the 30-year rolling average of the standard deviation and skewness of yearly temperature, respectively. All the interactions and additional covariates display non significant results. Given the larger set of covariates, the estimation losses some power, in particular in columns (2) and (3). Column (5) considers the baseline specification, but uses a third order polynomial. The intercept of the damage function and the optimal level of temperature are roughly the same.

Table 17 employs the main specification, but modifies the definition of the input factors. Column (1) displays the baseline results. Column (2) replaces the real capital services with a measure of real capital stock. A formal definition of the construction of such measures is presented in Appendix A.8.2. Column (3) substitutes the number of persons engaged with the number of hours worked. The economy-wide number of hours per worker is taken from the PWT database. Column (4) replaces the number of persons engaged with a measure of human capital, constructed according to Caselli (2005). More specifically, human capital, h, is a piece-wise function of the average years of schooling, s, which is obtained from PWT,

$$h = \exp\left(\phi(s)\right), \quad \phi(s) = \begin{cases} 0.13 & \text{if} \quad s \leq 4 \\ 0.10 & \text{if} \quad 4 < s \leq 8 \\ 0.07 & \text{if} \quad 8 < s \end{cases} .$$

Column (5) replicates the baseline specification, omitting the observations from India and China. Table 18 modifies the time trends and observational weights of the main specifications. Column (2) deems a quadratic market-specific time trend. Column (3) considers a linear trend at the sector- and continent-level. Column (4) and (5) contemplate same weights and GDP weights, respectively. The results across the different robustness exercises of Tables 17 and 18 are in line with the baseline results.

The baseline specification considers that changes in temperature only affect the level of productivity, ignoring the potential effects on its growth rate. If temperature permanently affects income through growth effects, this would have larger consequences for the projected long run effects of climate change, as small changes in annual growth rates accumulated over long periods imply larger effects on production and consequently welfare.

To test for growth effects, I employ the framework specified in Dell et al. (2012) and is inspired by Bond et al. (2010). To that end, I consider that both the level and the growth rate of productivity are functions of weather conditions,

$$\log\left(\Omega^{j}(T_t^r)\right) = \left(\tau_1^j \cdot T_t^r + \tau_2^j \cdot (T_t^r)^2 + \rho_1^j \cdot P_t^r + \rho_2^j \cdot (P_t^r)^2\right) + \iota^{jr} + \iota_t^{js} + \log\left(g_t^{\Omega,jr}\right), \tag{39}$$

$$\Delta\log\left(g_t^{\Omega,jr}\right) = \iota^{jr} + \vartheta_1^j \cdot T_t^r + \vartheta_2^j \cdot (T_t^r)^2 + \varrho_1^j \cdot P_t^r + \varrho_2^j \cdot (P_t^r)^2. \tag{40}$$

I differentiate equation (39) with respect to time and substitute the weather structure of equation (40), to obtain the following structure for the growth rate of productivity:

$$\begin{aligned}\Delta\log\left(\Omega^{j}(T_t^r)\right) = {} & \tau_1^j \cdot \Delta T_t^r + \vartheta_1^j \cdot T_t^r + \tau_2^j \cdot \Delta\left(T_t^r\right)^2 + \vartheta_2^j \cdot \left(T_t^r\right)^2 \\ & + \rho_1^j \cdot \Delta P_t^r + \varrho_1^j \cdot P_t^r + \rho_2^j \cdot \Delta\left(P_t^r\right)^2 + \varrho_2^j \cdot \left(P_t^r\right)^2 + \iota^{jr} + \iota_t^{js}\end{aligned} \tag{41}$$

Observe that equation (41) collapses to the time difference of equation (34) in the absence of growth effects, $\vartheta_1^j = \vartheta_2^j = \varrho_1^j = \varrho_2^j = 0$. Table 19 shows the results of the estimation. The impact of temperature on the levels on productivity construction are smaller than the results of the main specification, although with a higher uncertainty. Since no significant effects occur in terms of the growth rate, the main specification abstracts away from this channel.

A.9 Productivities and Amenities

Figures 16, 17 and 18 show the goodness of the fit of the market-specific productivity growth rate estimation. The bubbles indicate the yearly growth rate of real value added in the data and the growth rate of utility in the model in each sector-region pair. The bubbles size represent the market-specific employment.

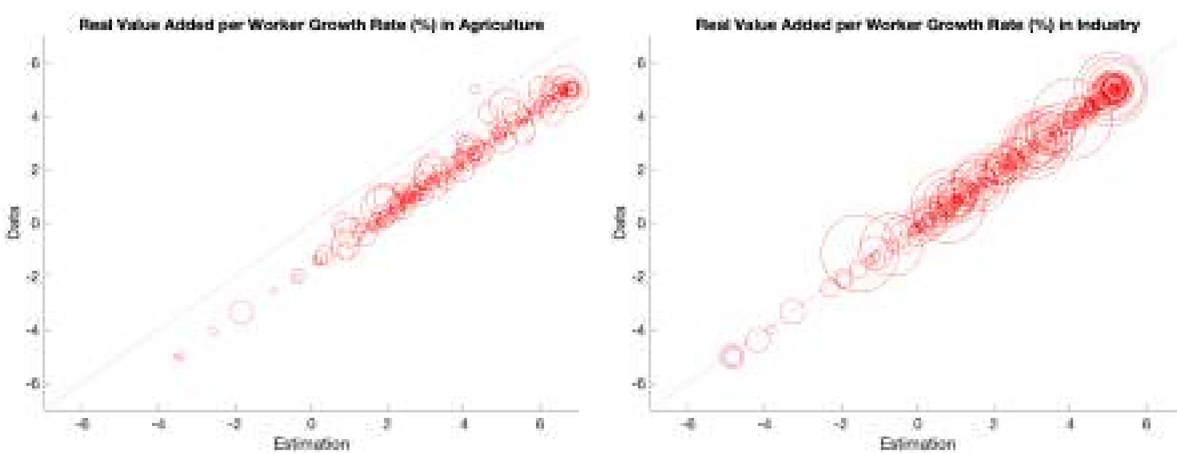

Figure 16: Real value added per worker growth rate for agriculture and industry: estimation and data.

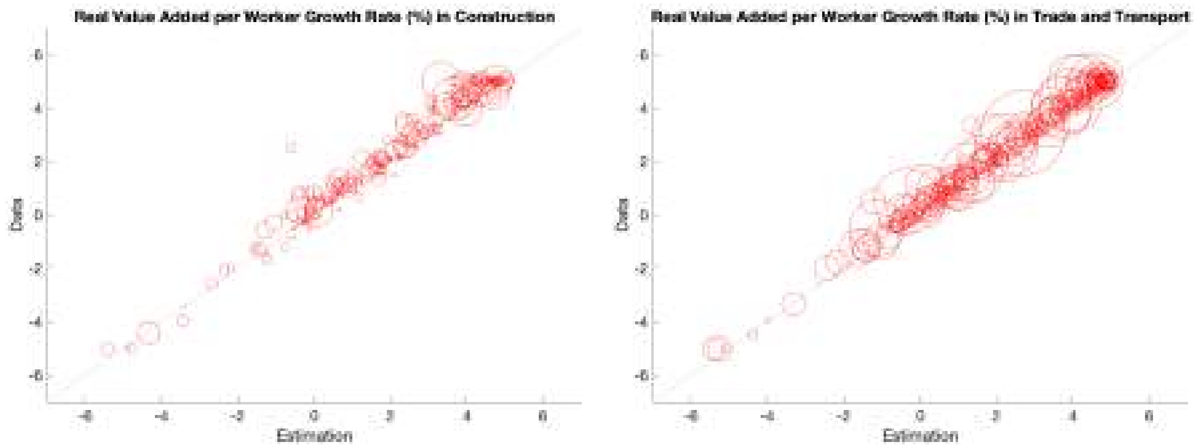

Figure 17: Real value added per worker growth rate for construction and trade and transportation: estimation and data.

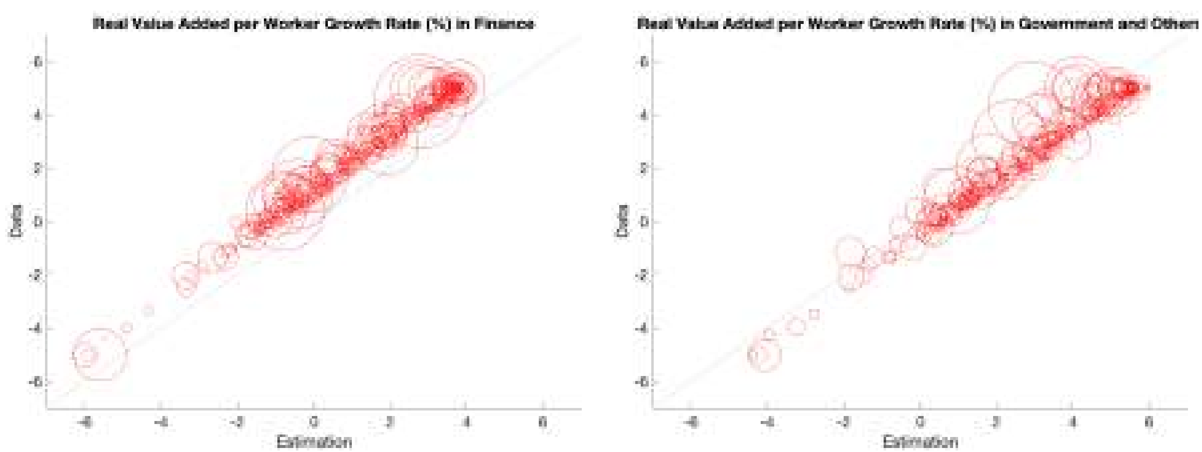

Figure 18: Real value added per worker growth rate for finance and government and other services: estimation and data.

COICOP		Sector Classification					
Code	Name	AGR	IND	CON	TRD	FIN	OTH
10	Food and non-alcoholic beverages	0.25	0.75	0	0	0	0
11	Food	0.25	0.75	0	0	0	0
12	Non-alcoholic beverages	0.25	0.75	0	0	0	0
20	Alcoholic beverages, tobacco and narcotics	0.25	0.75	0	0	0	0
21	Alcoholic beverages	0.25	0.75	0	0	0	0
22	Tobacco	0.25	0.75	0	0	0	0
23	Narcotics	0.25	0.75	0	0	0	0
30	Clothing and footwear	0	1	0	0	0	0
31	Clothing	0	1	0	0	0	0
32	Footwear	0	1	0	0	0	0
40	Housing, water, electricity, gas and other fuels	0	0.22	0.42	0	0.36	0
41	Actual rentals for housing	0	0	0.5	0	0.5	0
42	Imputed rentals for housing	0	0	0.5	0	0.5	0
43	Maintenance and repair of the dwelling	0	0	1	0	0	0
44	Water supply and miscellaneous dwelling services	0	0.5	0.5	0	0	0
45	Electricity, gas and other fuels	0	1	0	0	0	0
50	Furnishings, households equipment and routine maintenance	0	0.82	0	0.18	0	0
51	Furniture and furnishings, carpets and other floor coverings	0	1	0	0	0	0
52	Household textiles	0	1	0	0	0	0
53	Household appliances	0	1	0	0	0	0
54	Glassware, tableware and household utensils	0	1	0	0	0	0
55	Tools and equipment for house and garden	0	1	0	0	0	0
56	Goods and services for routine household maintenance	0	0.5	0	0.5	0	0
60	Health	0	0.33	0	0	0	0.67
61	Medical products, appliances and equipment	0	1	0	0	0	0
62	Out-patient services	0	0	0	0	0	1
63	Hospital services	0	0	0	0	0	1
70	Transport	0	0.27	0	0.73	0	0
71	Purchase of vehicles	0	1	0	0	0	0
72	Operation of personal transport equipment	0	0	0	1	0	0
73	Transport services	0	0	0	1	0	0
80	Communications	0	0.12	0	0.88	0	0
81	Postal services	0	0	0	1	0	0
82	Telephone and telefax equipment	0	1	0	0	0	0
83	Telephone and telefax services	0	0	0	1	0	0
90	Recreation and culture	0	0.58	0	0.06	0	0.35
91	Audio-visual, photographic and information processing equipment	0	1	0	0	0	0
92	Other major durables for recreation and culture	0	1	0	0	0	0
93	Other recreational items and equipment, gardens and pets	0	1	0	0	0	0
94	Recreational and cultural services	0	0	0	0	0	1
95	Newspapers, books and stationery	0	1	0	0	0	0
96	Package holidays	0	0	0	1	0	0
100	Education	0	0	0	0	0	1
101	Pre-primary and primary education	0	0	0	0	0	1
102	Secondary education	0	0	0	0	0	1
103	Post-secondary non-tertiary education	0	0	0	0	0	1
104	Tertiary education	0	0	0	0	0	1
105	Education not defined by level	0	0	0	0	0	1
110	Restaurants and hotels	0	0	0	1	0	0
111	Catering services	0	0	0	1	0	0
112	Accommodation services	0	0	0	1	0	0
120	Miscellaneous goods and services	0	0.28	0	0	0.52	0.2
121	Personal care	0	1	0	0	0	0
122	Prostitution	0	0	0	0	0	1
123	Personal effects n. e. c.	0	1	0	0	0	0
124	Social protection	0	0	0	0	0	1
125	Insurance	0	0	0	0	1	0
126	Financial services n. e. c.	0	0	0	0	1	0
127	Other services n. e. c.	0	0	0	0	0	1

Table 7: Crosswalk between COICOP and ISIC.

Sector	EORA industry classification
Agriculture	Agriculture and fishing
Industry	Mining and quarrying, food and beverages, textiles and wearing apparel, wood and paper, petroleum, chemical and non-metallic mineral products, metal products, electrical and machinery, transport equipment, other manufacturing, recycling and electricity, gas and water
Construction	Construction
Trade and transportation	Maintenance and repair, wholesale trade, retail trade, hotels and restaurants, transport and post and telecommunications
Finance	Financial intermediation and business activities
Government and others	Public administration, education, health and other services, private households and others

Table 8: Mapping between industrial classification in the EORA database and the six sectors of interest.

Region	Countries
Central Africa	Angola, Central African Republic, Cameroon, Chad, DR Congo, Congo, Gabon and Sao Tome and Principe
Central America	Belize, Costa Rica, Guatemala, Honduras, Nicaragua, Panama and El Salvador
Canada	Canada
Caribbean	Aruba, Anguila, Netherlands Antilles, Antigua, Bahamas, Bermuda, Barbados, Cuba, Curacao, Cayman Islands, Dominica, Dominican Republic, Haiti, Jamaica, Trinidad and Tobago and British Virgin Islands
Central Europe	Austria, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Germany, Hungary, Liechtenstein, Moldova, Montenegro, Poland, Romania, Serbia and Slovenia
China	China, Hong Kong, Macao, Mongolia and Taiwan
Eastern Africa	Burundi, Cape Verde, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Mauritius, Malawi, Mayotte, Mozambique, Reunion, Rwanda, Somalia, Seychelles, Tanzania, Uganda, Zambia and Zimbabwe
India	Afghanistan, Bangladesh, Bhutan, India, Iran, Maldives, Myanmar, Nepal, Sri Lanka and Pakistan
Korea	Japan, North Korea and South Korea
Middle East	Bahrain, Cyprus, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, United Arab Emirates and Yemen
Mexico	Mexico
North Africa	Algeria, Egypt, Libya, Morocco, South Sudan, Sudan, Tunisia and Western Sahara
North Europe	Denmark, Finland, Ireland, Iceland, Norway, Sweden and United Kingdom
Oceania	Australia, Cook, Fiji, New Caledonia, New Zealand, Papua New Guinea, French Polynesia, Samoa and Vanuatu
Russia	Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Lithuania, Latvia, Russia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan
South Africa	Botswana, Lesotho, Namibia, South Africa and Swaziland
South America	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Peru, Paraguay, Suriname, Uruguay and Venezuela
South East Asia	Brunei, Indonesia, Cambodia, Laos, Malaysia, Philippines, Singapore, Thailand and Viet Nam
South Europe	Albania, Spain, Greece, Italy, Macedonia, Malta, Portugal, San Marino and Slovakia
Western Africa	Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Gambia, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone and Togo
Western Europe	Andorra, Belgium, France, Luxembourg, Monaco, Netherlands and Switzerland

Table 9: Aggregation of countries into regions used in the American Community Survey.

Sector	**ISIC 3.1**	**ISIC 4.0**	**NAICS**	**SIC**	**Census 90**
Agriculture	A-B	A	11	01-09	10-32
Mining	C	B	21	10-14	40-50
Manufacturing	D	C	31-33	20-39	100-392
Utilities	E	D-E	22	49	450-472
Construction	F	F	23	15-18	60
Trade	G-H	G,I	42, 44-45 72	50-59, 70, 75-76	500-691, 762-770
Transport	I	H,J	48-49, 51	40-48	400-442
Business	J-K	K-N	52-56	60-67, 73, 81	700-760, 841
Government	L-N	O-Q	61-62	80, 82, 91-97	812-870, 900-952
Others	O-P	R-U	71	72, 78-79, 83-89	761, 771-810, 871-893

Table 10: Sector classification across ISIC 3.0, ISIC 4.0, NAICS and SIC.

Source	Countries
GGDC 10-sector	Argentina (1950-2011), Bolivia (1950-2011), Botswana (1960-2011), Brazil (1950-2011), Chile (1950-2012), China (1950-2012), Colombia (1950-2011), Costa Rica (1950-2011), Denmark (1947-2011), Egypt (1947-2013), Ethiopia (1960-2012), France (1947-2011), Germany (1950-2010), Ghana (1960-2011), Hong Kong (1950-2011), India (1950-2012), Indonesia (1950-2012), Italy (1947-2011), Japan (1950-2012), Kenya (1960-2011), Malawi (1960-2011), Malaysia (1950-2011), Mauritius (1960-2012), Mexico (1950-2012), Morocco (1947-2012), Netherlands (1947-2011), Nigeria (1960-2011), Peru (1950-2011), Philippines (1950-2012), Senegal (1960-2010), Singapore (1950-2012), South Africa (1960-2011), South Korea (1950-2011), Spain (1947-2011), Sweden (1947-2011), Taiwan (1950-2012), Tanzania (1960-2011), Thailand (1950-2011), UK (1947-2011), USA (1947-2011), Venezuela (1950-2012) and Zambia (1960-2011)
OECD STAN	Australia (1970-2016), Austria (1976-2016), Belgium (1970-2016), Canada (1970-2016), Chile (1986-2016), Costa Rica (1987-2017), Czech Republic (1970-2016), Denmark (1970-2016), Estonia (1989-2016), Finland (1970-2016), France (1970-2016), Germany (1991-2016), Greece (1970-2017), Hungary (1991-2016), Iceland (1973-2016), Ireland (1971-2016), Israel (1995-2016), Italy (1970-2016), Japan (1970-2016), Latvia (1995-2017), Lithuania (1995-2016), Luxembourg (1985-2016), Mexico (1970-2016), Netherlands (1970-2016), New Zealand (1971-2016), Norway (1970-2017), Poland (1994-2017), Portugal (1977-2017), Slovakia (1990-2017), Slovenia (1995-2016), South Korea (1970-2016), Spain (1980-2017), Sweden (1970-2016), Switzerland (1970-2017), Turkey (1998-2016), UK (1970-2017) and USA (1970-2017)
EU KLEMS	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, UK and USA (1970-2015)
EASD	Botswana (1964-2015), Burkina Faso (1965-2015), Cameroon (1965-2015), Ethiopia (1961-2015), Ghana (1960-2015), Kenya (1960-2016), Lesotho (1964-2015), Malawi (1960-2015), Mauritius (1960-2016), Mozambique (1966-2015), Namibia (1960-2016), Nigeria (1960-2015), Rwanda (1966-2016), Senegal (1960-2014), South Africa (1960-2016), Tanzania (1960-2015), Uganda (1952-2015) and Zambia (1960-2015)
APO	Australia, Bahrain, Bangladesh, Bhutan, Brunei, Cambodia, China, Fiji, Hong Kong, India, Indonesia, Iran, Japan, Kuwait, Laos, Malaysia, Mongolia, Myanmar, Nepal, Oman, Pakistan, Philippines, Qatar, Saudi Arabia, Singapore, South Korea, Sri Lanka, Taiwan, Thailand, Turkey, UAE and Viet Nam (1970-2015)
BEA and CPS	Alabama, Alaska, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin and Wyoming (1977-2019)

Table 11: Data sources for value added and employment.

Parent region	Countries
Asia	Australia, Bahrain, Bangladesh, Bhutan, Brunei, Cambodia, China, Fiji, Hong Kong, India, Indonesia, Iran, Japan, Kuwait, Laos, Malaysia, Mongolia, Myanmar, Nepal, New Zealand, Oman, Pakistan, Philippines, Qatar, Saudi Arabia, Singapore, South Korea, Sri Lanka, Taiwan, Thailand, Turkey, United Arab Emirates and Viet Nam
Europe	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom
Latin America	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Mexico, Peru and Venezuela
Middle East and North Africa	Egypt, Israel, Morocco and Turkey
North America	Canada and United States (50 states plus District of Columbia)
Subsaharan Africa	Botswana, Burkina Faso, Cameroon, Ethiopia, Ghana, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda and Zambia

Table 12: Definition of continents and countries, as in Dell et al. (2012).

	Agriculture	**Mining**	**Manufacturing**	**Utilities**	**Construction**
τ_1^j	2.998**	-2.536	2.171*	-0.649	3.510**
	(1.268)	(1.641)	(1.280)	(1.965)	(1.451)
τ_2^j	-0.143***	0.0128	-0.0783*	-0.0360	-0.144**
	(0.0368)	(0.0652)	(0.0447)	(0.0756)	(0.0602)
ρ_1^j	0.132**	-0.0802	0.0176	-0.0612	0.0261
	(0.0660)	(0.0514)	(0.0404)	(0.0612)	(0.0531)
ρ_2^j	-0.000402**	0.000190	-0.000103	0.000112	-0.000140
	(0.000176)	(0.000140)	(0.000117)	(0.000172)	(0.000153)
N	4,765	4,251	4,736	4,728	4,771
R^2	0.315	0.263	0.455	0.291	0.371
$\mathcal{T}^{j,*}$	10.50	99.43	13.87	-9.03	12.21

Standard errors clustered by country and year-continent, as defined by Dell et al. (2012), in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Effect of temperature on productivity for goods sectors.

	Trade	**Transport**	**Finance**	**Government**	**Others**
τ_1^j	1.863	2.779*	0.108	1.128	0.758
	(1.291)	(1.653)	(1.384)	(1.113)	(1.145)
τ_2^j	-0.0950**	-0.0717	0.0163	-0.0473	-0.00601
	(0.0469)	(0.0467)	(0.0529)	(0.0466)	(0.0400)
ρ_1^j	-0.00763	-0.00128	0.0820	0.0108	0.0252
	(0.0288)	(0.0364)	(0.0576)	(0.0540)	(0.0366)
ρ_2^j	-0.0000335	-0.0000408	-0.000246*	-0.0000893	-0.0000942
	(0.0000833)	(0.000114)	(0.000147)	(0.000178)	(0.000110)
N	4,700	4,675	4,716	3,974	4,652
R^2	0.442	0.402	0.334	0.553	0.406
$\mathcal{T}^{j,*}$	9.80	19.38	-3.32	11.92	63.01

Standard errors clustered by country and year-continent, as defined by Dell et al. (2012), in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Effect of temperature on productivity for services sectors.

	Agriculture				
	Baseline	Avg Temp	Income	Lagged Temp	Lead Temp
τ_1^j	2.998**	3.411**	2.014	3.358***	-0.613
	(1.268)	(1.386)	(1.377)	(1.272)	(1.196)
τ_2^j	-0.143***	-0.130***	-0.107***	-0.141***	0.00816
	(0.0368)	(0.0426)	(0.0371)	(0.0418)	(0.0474)
ρ_1^j	0.132**	0.0196	0.0755*	0.142**	-0.0869
	(0.0660)	(0.196)	(0.0445)	(0.0580)	(0.0579)
ρ_2^j	-0.000402**	-0.000811	-0.000268**	-0.000436***	0.000228
	(0.000176)	(0.000825)	(0.000130)	(0.000158)	(0.000151)
$\tau_1^{TempAvg,j}$		0.143			
		(0.104)			
$\tau_2^{TempAvg,j}$		-0.00172			
		(0.00230)			
$\rho_1^{TempAvg,j}$		0.00820			
		(0.0102)			
$\rho_2^{TempAvg,j}$		0.00000672			
		(0.0000359)			
$\tau_1^{Inc,j}$			1.139		
			(1.250)		
$\tau_2^{Inc,j}$			-0.0176		
			(0.0319)		
$\rho_1^{Inc,j}$			-0.0950*		
			(0.0519)		
$\rho_2^{Inc,j}$			0.000232		
			(0.000146)		
$\tau_1^{Lag,j}$				1.010	
				(1.395)	
$\tau_2^{Lag,j}$				0.00343	
				(0.0428)	
$\rho_1^{Lag,j}$				0.0238	
				(0.0481)	
$\rho_2^{Lag,j}$				-0.0000733	
				(0.000135)	
N	4,765	4,765	4,765	4,765	4,713
R^2	0.3152	0.3221	0.3203	0.3168	0.3015
$\mathcal{T}^{j,*}$	10.50	13.13	9.38	11.93	37.55

Standard errors clustered by country and year-continent, as defined by Dell et al. (2012), in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Effect of temperature on agricultural productivity. Robustness on covariates and placebo test.

	Agriculture				
	Baseline	Temp Range	Temp Std	Temp Skew	Temp Cubic
τ_1^j	2.998**	4.183	4.787	3.260***	2.872*
	(1.268)	(4.989)	(4.977)	(1.231)	(1.683)
τ_2^j	-0.143***	-0.141	-0.154	-0.152***	-0.135
	(0.0368)	(0.107)	(0.107)	(0.0376)	(0.134)
ρ_1^j	0.132**	-0.0385	-0.0489	0.0401	0.159
	(0.0660)	(0.113)	(0.108)	(0.0604)	(0.109)
ρ_2^j	-0.000402**	0.0000554	0.0000814	-0.000230	-0.000617
	(0.000176)	(0.000323)	(0.000307)	(0.000160)	(0.000765)
$\tau_1^{TempRange,j}$		-0.00891			
		(0.186)			
$\tau_2^{TempRange,j}$		-0.00184			
		(0.00380)			
$\rho_1^{PrecRange,j}$		0.000784			
		(0.000668)			
$\rho_2^{PrecRange,j}$		-0.00000213			
		(0.00000185)			
$\tau_1^{TempStd,j}$			-0.0967		
			(0.510)		
$\tau_2^{TempStd,j}$			-0.00354		
			(0.0106)		
$\rho_1^{PrecStd,j}$			0.00244		
			(0.00190)		
$\rho_2^{PrecStd,j}$			-0.00000662		
			(0.00000526)		
$\tau_1^{TempSkew,j}$				1.497	
				(2.099)	
$\tau_2^{TempSkew,j}$				-0.0557	
				(0.0819)	
$\rho_1^{PrecSkew,j}$				0.113	
				(0.152)	
$\rho_2^{PrecSkew,j}$				-0.0000875	
				(0.000402)	
τ_3^j					-0.000150
					(0.00287)
ρ_3^j					0.000000495
					(0.00000175)
N	4,765	4,765	4,765	4,765	4,765
R^2	0.315	0.318	0.318	0.318	0.315
$\mathcal{T}^{j,*}$	10.50	14.80	15.51	10.70	10.49

Standard errors clustered by country and year-continent, as defined by Dell et al. (2012), in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Effect of temperature on agricultural productivity. Robustness on covariates.

Agriculture

	Baseline	Capital Stock	Hours Worked	Human Capital	No CHN IND
τ_1^j	2.998**	2.845**	2.994**	2.992**	2.101*
	(1.268)	(1.263)	(1.277)	(1.285)	(1.081)
τ_2^j	-0.143***	-0.140***	-0.141***	-0.140***	-0.0963***
	(0.0368)	(0.0367)	(0.0373)	(0.0375)	(0.0262)
ρ_1^j	0.132**	0.130*	0.135**	0.137**	0.0192
	(0.0660)	(0.0663)	(0.0669)	(0.0667)	(0.0340)
ρ_2^j	-0.000402**	-0.000397**	-0.000412**	-0.000419**	-0.0000927
	(0.000176)	(0.000176)	(0.000178)	(0.000177)	(0.0000941)
N	4,765	4,831	4,760	4,760	4,673
R^2	0.3152	0.3118	0.3155	0.3163	0.2314
$\mathcal{T}^{j,*}$	10.50	10.19	10.61	10.66	10.91

Standard errors clustered by country and year-continent, as defined by Dell et al. (2012), in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Effect of temperature on agricultural productivity. Robustness on definition of input factors.

Agriculture

	Baseline	$\gamma_1^{jr}t + \gamma_2^{jr}t^2$	$\gamma_1^{js}t$	Same Weight	Weight GDP
τ_1^j	2.998**	3.020**	2.947**	2.542*	2.918**
	(1.268)	(1.278)	(1.259)	(1.288)	(1.181)
τ_2^j	-0.143***	-0.141***	-0.141***	-0.0952***	-0.111***
	(0.0368)	(0.0365)	(0.0362)	(0.0336)	(0.0309)
ρ_1^j	0.132**	0.134**	0.132**	0.0572**	0.0563
	(0.0660)	(0.0674)	(0.0660)	(0.0287)	(0.0551)
ρ_2^j	-0.000402**	-0.000408**	-0.000403**	-0.000118	-0.000236
	(0.000176)	(0.000178)	(0.000175)	(0.0000750)	(0.000156)
N	4,765	4,765	4,765	4,765	4,765
R^2	0.3152	0.3272	0.3099	0.1828	0.2443
$\mathcal{T}^{j,*}$	10.50	10.69	10.45	13.35	13.18

Standard errors clustered by country and year-continent, as defined by Dell et al. (2012), in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: Effect of temperature on agricultural productivity. Robustness on time trends and observational weights.

	Agriculture	Industry	Construction	Trade and Transportation	Finance	Government and Others
τ_1^j	1.674	1.672	2.615*	2.357*	0.500	-0.0724
	(1.395)	(1.413)	(1.466)	(1.309)	(1.602)	(0.826)
τ_2^j	-0.134***	-0.0618	-0.0858	-0.0819**	0.0502	0.00465
	(0.0394)	(0.0410)	(0.0525)	(0.0371)	(0.0534)	(0.0227)
ϑ_1^j	2.528	-1.032	1.306	-0.458	-0.946	1.754
	(1.917)	(2.296)	(2.912)	(2.379)	(2.883)	(2.101)
ϑ_2^j	-0.0142	0.0148	-0.0912	-0.00839	-0.0582	-0.0713
	(0.0523)	(0.0621)	(0.0848)	(0.0680)	(0.0940)	(0.0628)
ρ_1^j	0.121*	-0.0464	-0.0596	-0.0404	0.0678	0.0178
	(0.0681)	(0.0523)	(0.0759)	(0.0281)	(0.0625)	(0.0232)
ρ_2^j	-0.000382**	0.0000271	0.0000336	0.0000270	-0.000249*	-0.000116
	(0.000184)	(0.000144)	(0.000227)	(0.0000825)	(0.000141)	(0.0000856)
ϱ_1^j	0.0162	0.0987	0.172	0.0671	0.0381	-0.00451
	(0.0373)	(0.106)	(0.127)	(0.0420)	(0.0828)	(0.0435)
ϱ_2^j	-0.0000178	-0.000150	-0.000337	-0.000111	-0.0000169	0.0000713
	(0.000113)	(0.000285)	(0.000366)	(0.000126)	(0.000246)	(0.000138)
N	4,765	4,736	4,771	4,700	4,716	4,737
R^2	0.318	0.448	0.385	0.483	0.341	0.490
$T^{*,Level}$	6.27	13.54	15.24	14.40	-4.98	7.79
$T^{*,Growth}$	89.31	34.80	7.16	-27.25	-8.13	12.30

Standard errors clustered by country and year-region, as defined by Dell et al. (2012), in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Effect of temperature on productivity levels and growth rates across economic sectors.

B Solution of the Model

This Appendix derives the solution of the model in levels and time differences, discusses in detail the procedure to construct migration flows and outlines the numerical algorithm to solve the model.

B.1 Solution of the Model

Worker's Cost Minimization Workers minimize expenditure subject to an utility level, implicitly defined as shown below,

$$\begin{aligned} w_t^{jr} &= \min \quad \sum_{\tilde{j}=1}^{J} p_t^{\tilde{j}r} c_t^{(jr)(\tilde{j})} \\ &\text{st} \quad \sum_{\tilde{j}=1}^{J} \left(\gamma^{\tilde{j}}\right)^{\frac{1}{\varsigma}} \left(c_t^{jr}\right)^{-\frac{\vartheta^{\tilde{j}}}{\varsigma}} \left(c_t^{(jr)(\tilde{j})}\right)^{\frac{\varsigma-1}{\varsigma}} = 1. \end{aligned}$$

I derive the optimality condition between consumption $c_t^{(jr)(\tilde{j})}$ and $c_t^{(jr)(\hat{j})}$,

$$c_t^{(jr)(\tilde{j})} = c_t^{(jr)(\hat{j})} \left(\frac{\gamma^{\tilde{j}}}{\gamma^{\hat{j}}}\right) \left(\frac{p_t^{\hat{j}r}}{p_t^{\tilde{j}r}}\right)^{\varsigma} (c_t^{jr})^{\vartheta^{\hat{j}}-\vartheta^{\tilde{j}}},$$

and use the utility function to derive the Hicksian demand,

$$\begin{aligned} c_t^{(jr)(\tilde{j})} &= \gamma^{\tilde{j}} \left(\frac{p_t^{\tilde{j}r}}{E_t^{jr}}\right)^{-\varsigma} (c_t^{jr})^{\vartheta^{\tilde{j}}}, \\ E_t^{jr} &= \left(\sum_{j=1}^{J} \gamma^{\tilde{j}} \left(c_t^{jr}\right)^{\vartheta^{\tilde{j}}} \left(p_t^{\tilde{j}r}\right)^{1-\varsigma}\right)^{\frac{1}{1-\varsigma}}. \end{aligned}$$

Then, I employ the definition of the minimum cost expenditure,

$$w_t^{jr} = \sum_{\tilde{j}=1}^{J} p_t^{\tilde{j}r} c_t^{(jr)(\tilde{j})} = \left(\sum_{\tilde{j}=1}^{J} \gamma^{\tilde{j}} \left(c_t^{jr}\right)^{\vartheta^{\tilde{j}}} \left(p_t^{\tilde{j}r}\right)^{1-\varsigma}\right)^{\frac{1}{1-\varsigma}},$$

to rewrite consumption, $c_t^{(jr)(\tilde{j})}$, and consumption shares, $s_t^{(jr)(\tilde{j})}$.

$$\begin{aligned} c_t^{(jr)(\tilde{j})} &= \gamma^{\tilde{j}} \left(\frac{p_t^{\tilde{j}r}}{w_t^{jr}}\right)^{-\varsigma} \left(c_t^{jr}\right)^{\vartheta^{\tilde{j}}}, \\ s_t^{(jr)(\tilde{j})} &= \frac{p_t^{\tilde{j}r} c_t^{(jr)(\tilde{j})}}{w_t^{jr}} = \gamma^{\tilde{j}} \left(\frac{p_t^{\tilde{j}r}}{w_t^{jr}}\right)^{1-\varsigma} \left(c_t^{jr}\right)^{\vartheta^{\tilde{j}}}. \end{aligned}$$

Worker's Migration Decision Workers face a forward-looking decision regarding where to reside and work in the next period, as defined in equation (3). I take the expectation over the preference shock,

$$\mathbb{E}v_t^{jr} = \log(B_t^{jr} c_t^{jr}) + \beta \mathbb{E}v_{t+1}^{jr} + \mathbb{E} \max_{j'r'} \left\{\epsilon_t^{j'r'} + \bar{\epsilon}_t^{(jr)(j'r')}\right\},$$

$$\bar{\epsilon}_t^{(jr)(j'r')} = \beta(\mathbb{E}v_{t+1}^{j'r'} - \mathbb{E}v_{t+1}^{jr}) - \chi^{(jr)(j'r')},$$

and define $\bar{\epsilon}_t^{(jr)(j'r')}$ as a non-stochastic and non-idiosyncratic variable summarizing the net benefit of moving from market jr to $j'r'$, that is, the increase in discounted welfare minus the mobility cost.

Under the assumption that the idiosyncratic shock follows a Gumbel distribution with location parameter $\bar{\gamma}$ and scale parameter $\bar{\gamma}\nu$, $\epsilon_t^{j'r'} \sim \text{Gumbel}(-\bar{\gamma}\nu, \nu)$, where $\bar{\gamma}$ is the Euler-Mascheroni constant and ν governs the dispersion of the idiosyncratic shock, the expected value function can be rewritten as follows,

$$\mathbb{E}v_t^{jr} = \log(B_t^{jr} c_t^{jr}) + \nu \left(\log \sum_{\tilde{j}=1}^{J} \sum_{\tilde{r}=1}^{R} \exp\left(\beta \mathbb{E}v_{t+1}^{\tilde{j}\tilde{r}} - \chi^{(jr)(\tilde{j}\tilde{r})}\right)^{1/\nu} \right).$$

The share of households moving from market jr to market $j'r'$ can be computed as follows,

$$\mu_t^{(jr)(j'r')} = \mathbb{P}\left(j'r' = \underset{\tilde{j}'\tilde{r}'}{\text{argmax}} \{\epsilon_t^{j'r'} + \bar{\epsilon}_t^{(jr)(\tilde{j}'\tilde{r}')}\} \right).$$

Firm's Problem The price of final good j in region r, p_t^{jr}, is a CES ideal price index of the price paid for each variety. Varieties are purchased from the region with lower cost inclusive of freight,

$$\begin{aligned}
p_t^{jr} &= \left(\int \tilde{p}_t^{jr}(z)^{1-\xi} dF(z) \right)^{\frac{1}{1-\xi}}, \\
\tilde{p}_t^{jr}(z) &= \min_{\tilde{r}} \left\{ \frac{1}{z} \varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \left(A_t^{j\tilde{r}} \Omega^j(T_t^{\tilde{r}}) \right)^{-(1-\omega^{jr})} \right\}.
\end{aligned}$$

Given the properties of the Fréchet distribution, with marginal distribution $F(z) = \exp(-z^{-\theta})$, the distribution of the final prices is given by,

$$\begin{aligned}
\mathbb{P}(\tilde{p}_t^{jr}(z) \geq p) &= \mathbb{P}\left(\min_{\tilde{r}} \left\{ \frac{1}{z} \varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \left(A_t^{j\tilde{r}} \Omega^j(T_t^{\tilde{r}}) \right)^{-(1-\omega^{jr})} \right\} \geq p \right) \\
&= \mathbb{P}\left(\bigcap_{\tilde{r}=1}^{R} \left\{ \frac{1}{z} \varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \left(A_t^{j\tilde{r}} \Omega^j(T_t^{\tilde{r}}) \right)^{-(1-\omega^{jr})} \right\} \geq p \ \forall \tilde{r} \right) \\
&= \prod_{\tilde{r}=1}^{R} \mathbb{P}\left(\left\{ \frac{1}{p} \varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \left(A_t^{j\tilde{r}} \Omega^j(T_t^{\tilde{r}}) \right)^{-(1-\omega^{jr})} \right\} \geq z \right) \\
&= \prod_{\tilde{r}=1}^{R} \exp\left(- \left\{ \frac{1}{p} \varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \left(A_t^{j\tilde{r}} \Omega^j(T_t^{\tilde{r}}) \right)^{-(1-\omega^{jr})} \right\}^{-\theta} \right).
\end{aligned}$$

Consequently, the price of final goods also follows a Fréchet distribution,

$$\begin{aligned}
\mathbb{P}(\tilde{p}_t^{jr}(z) \leq p) &= 1 - e^{-\Phi_t^{jr} p^{\theta}}, \\
\Phi_t^{jr} &= \sum_{\tilde{r}=1}^{R} \left(\varkappa_t^{j\tilde{r}} \kappa^{(j\tilde{r})(jr)} \right)^{-\theta} \left(A_t^{j\tilde{r}} \Omega^j(T_t^{\tilde{r}}) \right)^{\theta(1-\omega^{j\tilde{r}})}, \\
p_t^{jr} &= \Gamma\left(1 + \frac{1-\xi}{\theta}\right)^{\frac{1}{1-\xi}} \left(\sum_{\tilde{r}=1}^{R} \left(\varkappa_t^{j\tilde{r}} \kappa_t^{(j\tilde{r})(jr)} \right)^{-\theta} \left(A_t^{j\tilde{r}} \Omega^j(T_t^{\tilde{r}}) \right)^{\theta(1-\omega^{j\tilde{r}})} \right)^{-1/\theta}.
\end{aligned}$$

The share of goods of sector j consumed in region r that were produced in region $\tilde{r}$ can be computed as follows,

$$
\begin{aligned}
\pi_t^{(j\tilde{r})(jr)} &= \mathbb{P}\left(\tilde{r} = \underset{\hat{r}}{\operatorname{argmin}}\left\{p_t^{j\hat{r}}(z)\kappa^{(j\hat{r})(jr)}\right\}\right), \\
&= \frac{\left(\varkappa_t^{j\tilde{r}}\kappa_t^{(j\tilde{r})(jr)}\right)^{-\theta}\left(A_t^{j\tilde{r}}\Omega^j(T_t^{\tilde{r}})\right)^{\theta(1-\omega^{j\tilde{r}})}}{\sum_{\hat{r}=1}^{R}\left(\varkappa_t^{j\hat{r}}\kappa_t^{(j\hat{r})(jr)}\right)^{-\theta}\left(A_t^{j\hat{r}}\Omega^j(T_t^{\hat{r}})\right)^{\theta(1-\omega^{j\hat{r}})}}.
\end{aligned}
$$

B.2 Time Differences

To ease the exposition, let $\dot{x}_{t+1} = x_{t+1}/x_t$ be the proportional change of variable x from period t to $t+1$. Given an allocation of wages, labor, trade shares, consumption shares, fossil fuel expenditure in total energy, $\varrho_t = \{\varrho_t^{jr}\}_{j=1,r=1}^{J,R}$, and carbon stocks, $(w_t, L_t, \pi_t, s_t, \varrho_t, S_{1,t}, S_{2,t}, \Upsilon_t)$, and a change of the state variables $(\dot{L}_{t+1}, \dot{S}_{1,t+1}, \dot{S}_{2,t+1}, \dot{\Upsilon}_{t+1}, \dot{\Theta}_{t+1})$, the time difference of wages, rents, energy price, input bundle price, final good price and utility and the next period level of expenditure, trade shares and consumption shares, $(\dot{w}_{t+1}, \dot{q}_{t+1}, \dot{p}_{t+1}^e, \dot{\varkappa}_{t+1}, \dot{p}_{t+1}, \dot{u}_{t+1}, X_{t+1}, \pi_{t+1}, s_{t+1})$, solves the following system of equations,

$$
\dot{q}_{t+1}^r = \sum_{j=1}^{J}\phi_t^{jr}\dot{w}_{t+1}^{jr}\dot{L}_{t+1}^{jr}, \quad \text{with} \quad \phi_t^{jr} := \left(\frac{w_t^{jr}L_t^{jr}}{\sum_{\tilde{j}=1}^{J}\sum_{\tilde{r}=1}^{R}w_t^{\tilde{j}\tilde{r}}L_t^{\tilde{j}\tilde{r}}}\right), \tag{B.1}
$$

$$
\dot{p}_{t+1}^{e,jr} = \left(\varrho_t^{jr}\left(\dot{p}_{t+1}^{f,jr}\right)^{1-\zeta} + (1-\varrho_t^{jr})\left(\dot{p}_{t+1}^{c,jr}\right)^{1-\zeta}\right)^{1/(1-\zeta)}, \quad \text{with} \quad \varrho_t^{jr} = \frac{p_t^{f,jr}e_t^{f,jr}}{p_t^{jr}e_t^{jr}}, \tag{B.2}
$$

$$
\dot{\varkappa}_{t+1}^{jr} = \left(\left(\dot{w}_{t+1}^{jr}\right)^{\alpha^L}\left(\dot{q}_{t+1}^r\right)^{\alpha^H}\left(\dot{p}_{t+1}^{e,jr}\right)^{\alpha^E}\right)^{(1-\omega^{jr})/\alpha^W}\left(\prod_{\tilde{j}=1}^{J}\left(\dot{p}_{t+1}^{\tilde{j}r}\right)^{\omega^{(\tilde{j}r)(jr)}}\right)^{\omega^{jr}/\alpha^W}, \tag{B.3}
$$

$$
\dot{p}_{t+1}^{jr} = \left(\sum_{\tilde{r}=1}^{R}\pi_t^{(j\tilde{r})(jr)}\left(\dot{\varkappa}_{t+1}^{j\tilde{r}}\dot{\kappa}_{t+1}^{(j\tilde{r})(jr)}\right)^{-\theta}\left(\dot{A}_{t+1}^{j\tilde{r}}\dot{\Omega}^j\left(T_{t+1}^{\tilde{r}}\right)\right)^{\theta(1-\omega^{j\tilde{r}})}\right)^{-1/\theta}, \tag{B.4}
$$

$$
\pi_{t+1}^{(j\tilde{r})(jr)} = \pi_t^{(j\tilde{r})(jr)}\left(\dot{\varkappa}_{t+1}^{j\tilde{r}}\dot{\kappa}_{t+1}^{(j\tilde{r})(jr)}\right)^{-\theta}\left(\dot{A}_{t+1}^{j\tilde{r}}\dot{\Omega}^j\left(T_{t+1}^{\tilde{r}}\right)\right)^{\theta(1-\omega^{j\tilde{r}})}\left(\dot{p}_{t+1}^{jr}\right)^{-\theta}, \tag{B.5}
$$

$$
s_{t+1}^{(jr)(\tilde{j})} = s_t^{(jr)(\tilde{j})}\left(\frac{\dot{p}_{t+1}^{\tilde{j}r}}{\dot{w}_{t+1}^{jr}}\right)^{1-\varsigma}\left(\dot{u}_{t+1}^{jr}\right)^{\vartheta^{\tilde{j}}}, \quad \text{with} \quad \sum_{\tilde{j}=1}^{J}s_{t+1}^{(jr)(\tilde{j})} = 1, \tag{B.6}
$$

$$
\begin{aligned}
X_{t+1}^{jr} = {} & \sum_{\tilde{j}=1}^{J}s_{t+1}^{(\tilde{j}r)(j)}\dot{w}_{t+1}^{\tilde{j}r}w_t^{\tilde{j}r}\dot{L}_{t+1}^{\tilde{j}r}L_t^{\tilde{j}r} + s_{t+1}^{(jr)}\sum_{\tilde{j}=1}^{J}\left(\alpha^H/\alpha^L\right)\dot{w}_{t+1}^{\tilde{j}r}w_t^{\tilde{j}r}\dot{L}_{t+1}^{\tilde{j}r}L_t^{\tilde{j}r} \\
& + \sum_{\tilde{j}=1}^{J}\left(\omega^{(jr)(\tilde{j}r)}\omega^{\tilde{j}r}/\alpha^W\right)\sum_{\tilde{r}=1}^{R}\pi_{t+1}^{(\tilde{j}r)(\tilde{j}\tilde{r})}X_{t+1}^{\tilde{j}\tilde{r}},
\end{aligned} \tag{B.7}
$$

$$
\dot{w}_{t+1}^{jr} = \left(\alpha^L/\alpha^W\right)\left(1-\omega^{jr}\right)\left(\sum_{\tilde{r}=1}^{R}\pi_{t+1}^{(jr)(j\tilde{r})}X_{t+1}^{j\tilde{r}}\right)\left(w_{t+1}^{jr}\dot{L}_{t+1}^{jr}L_t^{jr}\right)^{-1}, \tag{B.8}
$$

$$
\dot{e}_{t+1}^{f,jr} = \left(\frac{\dot{w}_{t+1}^{jr}\dot{L}_{t+1}^{jr}}{\dot{p}_{t+1}^{f,jr}}\right)\left(\frac{\dot{p}_{t+1}^{f,jr}}{\dot{p}_{t+1}^{e,jr}}\right)^{1-\zeta}, \tag{B.9}
$$

$$
\dot{e}_{t+1}^{c,jr} = \left(\frac{\dot{w}_{t+1}^{jr}\dot{L}_{t+1}^{jr}}{\dot{p}_{t+1}^{c,jr}}\right)\left(\frac{\dot{p}_{t+1}^{c,jr}}{\dot{p}_{t+1}^{e,jr}}\right)^{1-\zeta}. \tag{B.10}
$$

To ensure that the economic and climate variables converge to a steady state, I impose that the sequence of changes in fundamentals converges to one in the long-run, $\lim_{t\to\infty}\dot{\Theta}_{t+1} = 1$, and require that the exogenous projections of carbon dioxide emissions and forcing of other greenhouse gases converge to zero over time, $\lim_{t\to\infty} E^x_{t+1} = \lim_{t\to\infty} F^x_{t+1} = 0$. Given the structure of the energy and climate model, the aforementioned assumptions imply that global and local levels of temperature reach a steady state over time. Consequently, the damage function on productivity evaluated at local temperature, $\Omega^j(T^r_{t+1})$, also converges to a constant value over time and the exogenous and endogenous variation of productivities converge to a constant value in the long-run.

Given data on wages, labor, trade shares, consumption shares, fossil fuel expenditure in total energy, migration shares and carbon stocks in the initial period $(w_0, L_0, \pi_0, s_0, \varrho_0, \mu_{-1}, S_{1,0}, S_{2,0}, \Upsilon_0)$, and a converging sequence of fundamental and exogenous climate variables $\{\Theta_{t+1}, E^x_{t+1}, F^x_{t+1}\}^{\infty}_{t=0}$, the sequence of $\{\mu_{t+1}, L_{t+1}, \upsilon_{t+1}, S_{1,t+1}, S_{2,t+1}, T_{t+1}, T^r_{t+1}, \Upsilon_{t+1}\}^{\infty}_{t=0}$ solve the following system of equations,

$$\mu^{(jr)(j'r')}_{t+1} = \frac{\mu^{(jr)(j'r')}_t \dot{\Xi}^{(jr)(j'r')}_t \left(\dot{\upsilon}^{j'r'}_{t+2}\right)^{\beta}}{\sum_{\tilde{j}=1}^{J}\sum_{\tilde{r}=1}^{R} \mu^{(jr)(\tilde{j}\tilde{r})}_t \dot{\Xi}^{(jr)(\tilde{j}\tilde{r})}_t \left(\dot{\upsilon}^{\tilde{j}\tilde{r}}_{t+2}\right)^{\beta}}, \tag{B.11}$$

$$L^{j'r'}_{t+1} = \sum_{j=1}^{J}\sum_{r=1}^{R} L^{jr}_t \mu^{(jr)(j'r')}_t, \tag{B.12}$$

$$\dot{\upsilon}^{jr}_{t+1} = \left(\dot{B}^{jr}_{t+1}\dot{w}^{jr}_{t+1}\right)^{1/\nu} \left(\sum_{j'=1}^{J}\sum_{r'=1}^{R} \mu^{(jr)(j'r')}_t \dot{\Xi}^{(jr)(j'r')}_{t+1} \left(\dot{\upsilon}^{j'r'}_{t+2}\right)^{\beta}\right), \tag{B.13}$$

as well as equations (21), (22), (23), (25) and (26). Where the variables $\upsilon_t = \{\exp(V^{jr}_t)^{1/\nu}\}^{J,R}_{j=1,r=1}$ and $\Xi_t = \{\exp(\chi^{(jr)(j'r')}_t)^{-1/\nu}\}^{J,R}_{j=1,r=1}$ denote transformations of the value function and the migration costs, respectively.

B.3 Migration Elasticity

In the subsequent derivations, I assume that the mobility costs are time-invariant, $\chi^{(jr)(j'r')}_t = \chi^{(jr)(j'r')}$.

PPML regression stage The first stage is a fixed-effect estimation to compute the value function. I multiply and divide the mass of workers migrating across market by $\exp(-\beta V^{jr}_{t+1})^{1/\nu}$, as shown below,

$$\begin{aligned}
\mu^{(jr)(j'r')}_t L^{jr}_t &= \frac{\exp\left(\beta V^{j'r'}_{t+1} - \chi^{(jr)(j'r')}\right)^{1/\nu}}{\sum_{\tilde{j}=1}^{J}\sum_{\tilde{r}=1}^{R} \exp\left(\beta V^{\tilde{j}\tilde{r}}_{t+1} - \chi^{(jr)(\tilde{j}\tilde{r})}\right)^{1/\nu}} L^{jr}_t \\
&= \frac{\exp\left(\beta\left(V^{j'r'}_{t+1} - V^{jr}_{t+1}\right) - \chi^{(jr)(j'r')}\right)^{1/\nu}}{\sum_{\tilde{j}=1}^{J}\sum_{\tilde{r}=1}^{R} \exp\left(\beta\left(V^{\tilde{j}\tilde{r}}_{t+1} - V^{jr}_{t+1}\right) - \chi^{(jr)(\tilde{j}\tilde{r})}\right)^{1/\nu}} L^{jr}_t.
\end{aligned}$$

Then, I gather terms and use the definition of the option value of migration to rewrite this equation as follows,

$$
\begin{aligned}
\mu_t^{(jr)(j'r')} L_t^{jr} &= \frac{\exp\left(\beta\left(V_{t+1}^{j'r'} - V_{t+1}^{jr}\right) - \chi^{(jr)(j'r')}\right)^{1/\nu}}{\sum_{\tilde{j}=1}^{J}\sum_{\tilde{r}=1}^{R}\exp\left(\beta\left(V_{t+1}^{\tilde{j}\tilde{r}} - V_{t+1}^{jr}\right) - \chi^{(jr)(\tilde{j}\tilde{r})}\right)^{1/\nu}} L_t^{jr} \\
&= \exp\left(\beta\left(V_{t+1}^{j'r'} - V_{t+1}^{jr}\right) - \chi^{(jr)(j'r')} - \frac{1}{\nu}\Lambda_{t+1}^{jr} + \log(L_t^{jr})\right)^{1/\nu} \\
&= \exp\left(\beta\left(V_{t+1}^{j'r'} - V_{t+1}^{11}\right) - \beta\left(V_{t+1}^{jr} - V_{t+1}^{11}\right) - \chi_t^{(jr)(j'r')} - \frac{1}{\nu}\Lambda_{t+1}^{jr} + \log(L_t^{jr})\right)^{1/\nu} \\
&= \exp\left(\mathcal{D}_t^{j'r'} + \mathcal{O}_t^{jr} - \frac{1}{\nu}\chi_t^{(jr)(j'r')}\right) + \xi_t^{(jr)(j'r')}, \\
\mathcal{D}_t^{j'r'} &:= \frac{\beta}{\nu}(V_{t+1}^{j'r'} - V_{t+1}^{11}), \\
\mathcal{O}_t^{jr} &:= -\frac{\beta}{\nu}(V_{t+1}^{jr} - V_{t+1}^{11}) + \log\left(L_t^{jr}\right) - \frac{1}{\nu}\Lambda_{t+1}^{jr}, \\
\Lambda_t^{jr} &:= \nu\log\left(\sum_{j'=1}^{J}\sum_{r'=1}^{R}\exp\left(\beta\left(V_{t+1}^{j'r'} - V_{t+1}^{jr}\right) - \chi_t^{(jr)(j'r')}\right)^{1/\nu}\right)
\end{aligned}
$$

where $\mathcal{D}_t^{j'r'}$ is a destination-time fixed effect, $\mathcal{O}_t^{jr}$ is an origin-time fixed effect and $\xi_t^{(jr)(j'r')}$ is the sampling error. The terms $\mathcal{D}_t^{j'r'}$ and $\mathcal{O}_t^{jr}$ are not separately identified, so without loss of generality I set $\mathcal{D}_t^{11} = 0$. Equation (32) is estimated by PPML.

Bellman regression stage The second stage formulates the Bellman equation as an estimating equation using the destination- and origin-time fixed effects, $\mathcal{D}_t^{j'r'}$ and $\mathcal{O}_{t+1}^{jr}$, of the previous step. To construct the estimating equation, I manipulate the value function of period $t+1$ as follows,

$$
\begin{aligned}
\frac{\beta}{\nu}V_{t+1}^{jr} &= \frac{\beta}{\nu}\log(B_{t+1}^{jr}u_{t+1}^{jr}) + \frac{\beta^2}{\nu}V_{t+2}^{jr} - \frac{\beta}{\nu}\chi^{(jr)(jr)} + \frac{\beta}{\nu}\Lambda_{t+1}^{jr} \\
\frac{\beta}{\nu}(V_{t+1}^{jr} - V_{t+1}^{11}) - \frac{\beta^2}{\nu}(V_{t+2}^{jr} - V_{t+2}^{11}) - \frac{\beta}{\nu}\Lambda_{t+1}^{jr} &= \frac{\beta}{\nu}(\beta V_{t+2}^{11} - V_{t+1}^{11}) - \frac{\beta}{\nu}\chi^{(jr)(jr)} + \frac{\beta}{\nu}\log(B_{t+1}^{jr}u_{t+1}^{jr}) \\
\mathcal{D}_t^{jr} + \beta\mathcal{O}_{t+1}^{jr} - \beta\log(L_{t+1}^{jr}) &= \frac{\beta}{\nu}\left(\beta V_{t+2}^{11} - V_{t+1}^{11}\right) - \frac{\beta}{\nu}\chi^{(jr)(jr)} + \frac{\beta}{\nu}\log(B_{t+1}^{jr}u_{t+1}^{jr}).
\end{aligned}
$$

The variable in the left-hand side is constructed with the results of the first stage and data on population and the first term on the right-hand side is a time fixed effect and the second term is a market fixed effect when assuming migration frictions do not vary over time.

B.4 Welfare

Workers' Welfare The lifetime utility of a worker, V_0^{jr}, in sector j and region r is defined as follows,

$$
V_0^{\prime jr} = \log\left(B_0^{jr}c_0^{\prime jr}\right) + \beta V_1^{\prime jr} - \nu\log\left(\mu_0^{\prime(jr)(jr)}\right) = \sum_{t=0}^{\infty}\beta^t\log\left(\frac{B_t^{jr}c_t^{\prime jr}}{\left(\mu_t^{\prime(jr)(jr)}\right)^{\nu}}\right).
$$

Thus, I define the equivalent variation for an average worker as the scalar $\mathcal{E}_t^{jr}$ that satisfies:

$$
\begin{aligned}
V_0^{\prime jr} &= V_0^{jr} + \sum_{t=0}^{\infty} \beta^t \log\left(\mathcal{E}^{jr}\right), \\
\log\left(\mathcal{E}^{jr}\right) &= (1-\beta)\left(V_0^{\prime jr} - V_0^{jr}\right) \\
&= (1-\beta)\sum_{t=0}^{\infty}\beta^t \log\left(\frac{c_t^{\prime jr}/c_t^{jr}}{\left(\mu_t^{\prime (jr)(jr)}/\mu_t^{(jr)(jr)}\right)^{\nu}}\right) \\
&= \sum_{t=0}^{\infty}\beta^t \log\left(\frac{c_t^{\prime jr}/c_t^{jr}}{\left(\mu_t^{\prime (jr)(jr)}/\mu_t^{(jr)(jr)}\right)^{\nu}}\right) - \sum_{t=0}^{\infty}\beta^{t+1} \log\left(\frac{c_t^{\prime jr}/c_t^{jr}}{\left(\mu_t^{\prime (jr)(jr)}/\mu_t^{(jr)(jr)}\right)^{\nu}}\right) \\
&= \log\left(\frac{u_0^{\prime jr}/u_0^{jr}}{\left(\mu_0^{\prime (jr)(jr)}/\mu_0^{(jr)(jr)}\right)^{\nu}}\right) + \sum_{t=1}^{\infty}\beta^t \log\left(\frac{\left(c_t^{\prime jr}/c_t^{jr}\right)/\left(u_{t-1}^{\prime jr}/u_{t-1}^{jr}\right)}{\left(\left(\mu_t^{\prime (jr)(jr)}/\mu_t^{(jr)(jr)}\right)/\left(\mu_{t-1}^{\prime (jr)(jr)}/\mu_{t-1}^{(jr)(jr)}\right)\right)^{\nu}}\right) \\
&= \sum_{t=1}^{\infty}\beta^t \log\left(\frac{\dot{u}_t^{\prime jr}/\dot{u}_t^{jr}}{\left(\dot{\mu}_t^{\prime (jr)(jr)}/\dot{\mu}_t^{(jr)(jr)}\right)^{\nu}}\right)
\end{aligned}
$$

Hence, the workers' equivalent variation depends on the change in real consumption and the change in the option value. When warming makes a market less suitable for residing and producing, the share of households that decide to stay in this region is expected to decrease. Hence, migration acts as a mitigation mechanism against global warming, attenuating the welfare losses.

For simplicity in the exposition, define the hat notation, $\hat{x}_{t+1} = \dot{x}'_{t+1}/\dot{x}_{t+1}$, as the ratio of the counterfactual and factual time differences. The change in real consumption can be derived by manipulating equation (B.6),

$$
\begin{aligned}
\left(\hat{w}_{t+1}^{jr}\right)^{1-\varsigma} &= \sum_{\tilde{\jmath}=1}^{J}\left(\frac{1}{\sum_{\tilde{\jmath}=1}^{J} s_t^{(jr)(\tilde{\jmath})}\left(\dot{p}_{t+1}^{\tilde{\jmath}r}\right)^{1-\varsigma}\left(\dot{u}_{t+1}^{jr}\right)^{\vartheta^{\tilde{\jmath}}}}\right) s_t^{\prime (jr)(\tilde{\jmath})}\left(\dot{p}_{t+1}^{\prime \tilde{\jmath}r}\right)^{1-\varsigma}\left(\dot{u}_{t+1}^{\prime jr}\right)^{\vartheta^{\tilde{\jmath}}} \\
&= \sum_{\tilde{\jmath}=1}^{J}\left(\frac{1}{\dot{w}_{t+1}^{jr}}\right)^{1-\varsigma} s_t^{\prime (jr)(\tilde{\jmath})}\left(\dot{p}_{t+1}^{\prime \tilde{\jmath}r}\right)^{1-\varsigma}\left(\dot{u}_{t+1}^{\prime jr}\right)^{\vartheta^{\tilde{\jmath}}} \\
&= \sum_{\tilde{\jmath}=1}^{J} s_{t+1}^{(jr)(\tilde{\jmath})}\left(\frac{s_t^{\prime (jr)(\tilde{\jmath})}}{s_t^{(jr)(\tilde{\jmath})}}\right)\left(\hat{p}_{t+1}^{\tilde{\jmath}r}\right)^{1-\varsigma}\left(\hat{u}_{t+1}^{jr}\right)^{\vartheta^{\tilde{\jmath}}} \\
&= \sum_{\tilde{\jmath}=1}^{J} s_{t+1}^{(jr)(\tilde{\jmath})}\left(\hat{s}_{t+1}^{(jr)(\tilde{\jmath})}\right)^{-1}\left(\hat{p}_{t+1}^{\tilde{\jmath}r}\right)^{1-\varsigma}\left(\hat{u}_{t+1}^{jr}\right)^{\vartheta^{\tilde{\jmath}}}.
\end{aligned}
$$

Therefore, in this model, the change in real consumption does not only depend on the variations on wages and prices, but also on the variations of consumption shares. When warming rises the consumption share of the most affected goods (e.g., agriculture), real consumption further declines. Hence, non homotheticities act as a magnification mechanism, aggravating welfare losses.[64] Finally, as in Caliendo et al. (2017), the change in the price of goods depends on the change in trade openness, factor costs and fundamental

[64]Observe that in the particular case in which preferences replicate a Cobb Douglas structure with $\vartheta^{\tilde{\jmath}} = 1-\varsigma$ and $\varsigma \to 1$, the change in real consumption is given by $\hat{u}_{t+1}^{jr} = \hat{w}_{t+1}^{jr}/\prod_{\tilde{\jmath}=1}^{J}\left(\hat{p}_{t+1}^{\tilde{\jmath}r}\right)^{s_{t+1}^{(jr)(\tilde{\jmath})}}$, where $s_{t+1}^{(jr)(\tilde{\jmath})}$ is a time-invariant constant.

productivity,

$$\hat{p}_{t+1}^{\tilde{\jmath}r} = \left(\hat{\pi}_{t+1}^{(\tilde{\jmath}r)(\tilde{\jmath}r)}\right)^{1/\theta} \left(\frac{\hat{x}_{t+1}^{\tilde{\jmath}r}}{\hat{\Omega}^{\tilde{\jmath}}\left(T_{t+1}^{r}\right)}\right).$$

The change in prices can be decomposed in three terms. First, the direct change in fundamental productivity, which captures the sign and size of the warming impact. Second, change in the trade share with itself, which evaluates the change in trade openness, that gives households access to cheaper imported goods. When warming makes a particular region relatively less productive, it is expected to purchase less varieties from itself and more from other trade partners, decreasing the trade share with itself and attenuating welfare losses. Finally, change in factor prices, which captures the effect of local factors and input output linkages. When warming rises the prices of the most affected products, other products will experience augments in prices depending on the particular composition of the input output linkages.

Figures 19-24 zoom in the spatial pattern and distribution function of welfare losses in United States, Canada, China, India, Russia and Brazil.

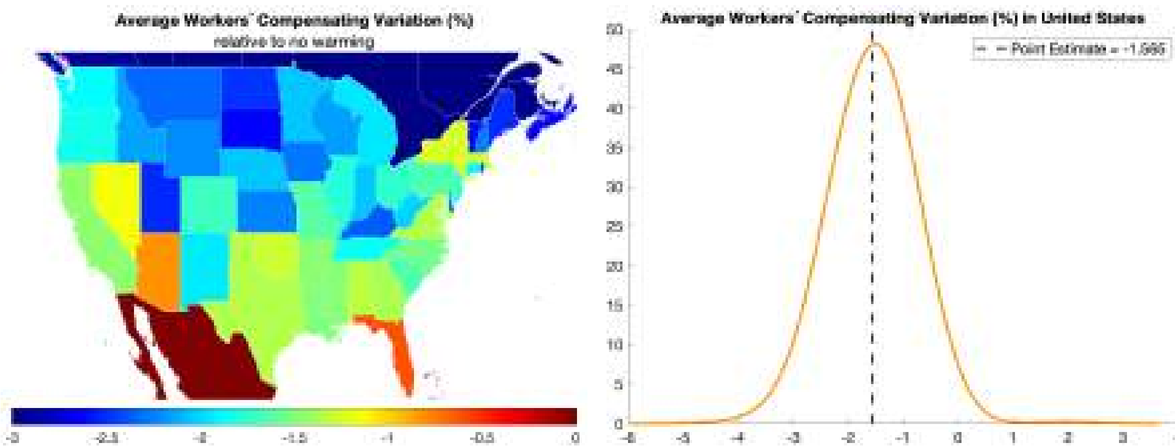

Figure 19: Average workers' welfare losses due to global warming in United States.

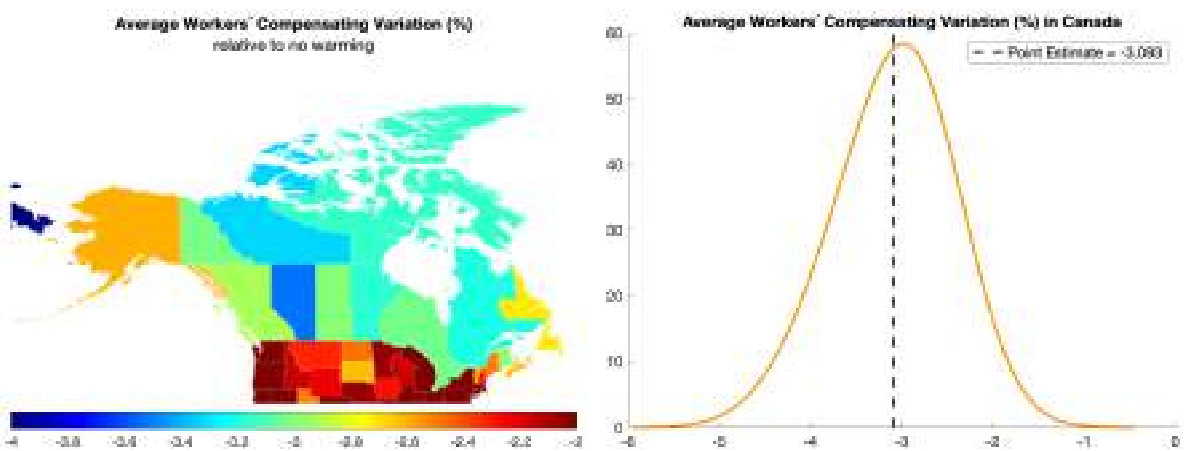

Figure 20: Average workers' welfare losses due to global warming in Canada.

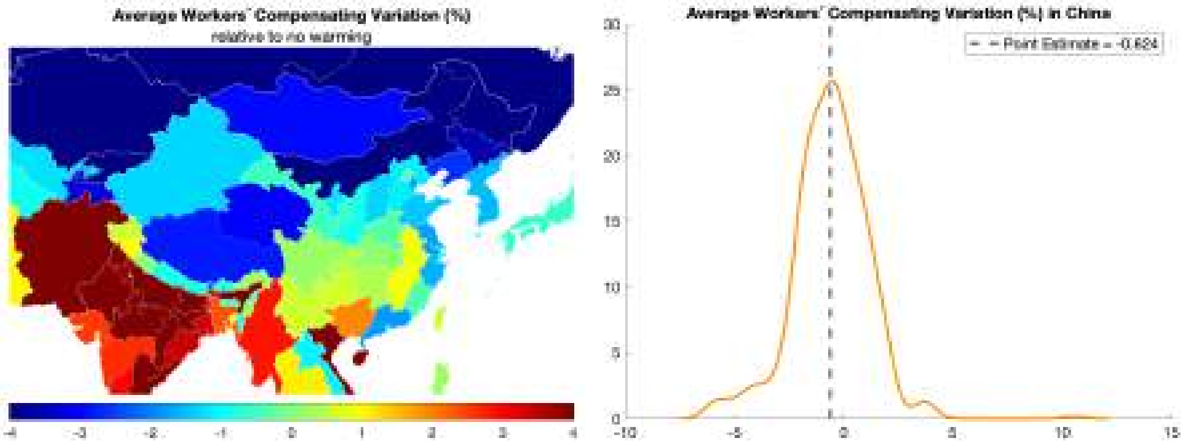

Figure 21: Average workers' welfare losses due to global warming in China.

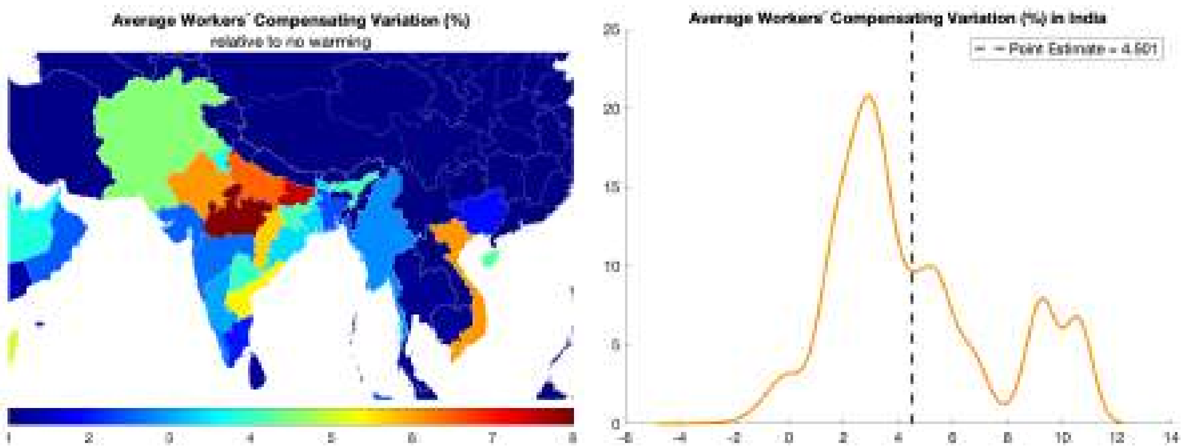

Figure 22: Average workers' welfare losses due to global warming in India.

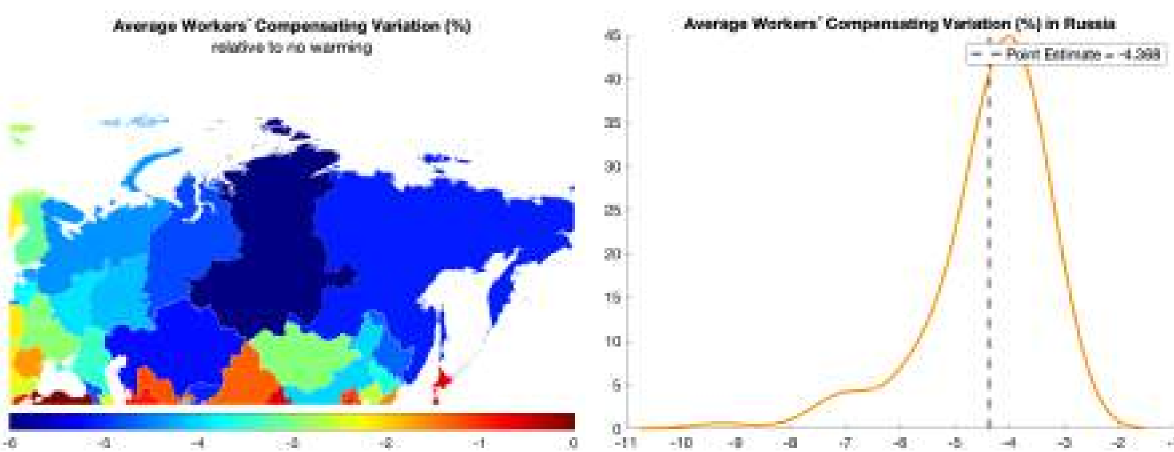

Figure 23: Average workers' welfare losses due to global warming in Russia.

Average Workers' Welfare The lifetime utility of an average worker, V_0^r, in region r is defined as the weighted average of lifetime utilities across working sectors, where weights are the employment shares,

$$V_0^r = \sum_{j=1}^{J} \left(\frac{L_0^{jr}}{L_0^r} \right) V_0^{jr}.$$

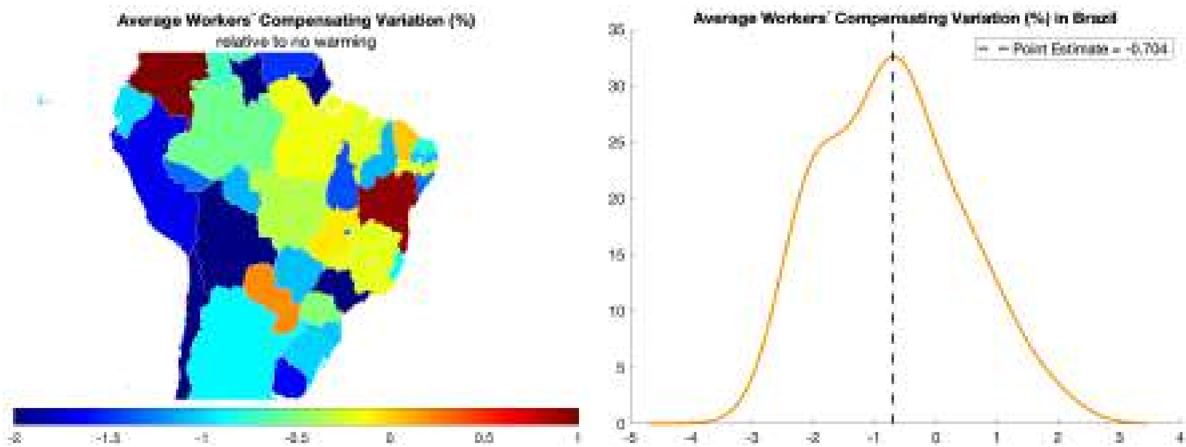

Figure 24: Average workers' welfare losses due to global warming in Brazil.

Thus, I define the equivalent variation for an average worker as the scalar $\mathcal{E}^r$ that satisfies:

$$V_0'^r = V_0^r + \sum_{t=0}^{\infty} \beta^t \log\left(\mathcal{E}^r\right),$$

$$\log\left(\mathcal{E}^r\right) = (1-\beta)\left(V_0'^r - V_0^r\right) = (1-\beta)\sum_{j=1}^{J}\left(\frac{L_0^{jr}}{L_0^r}\right)\left(V_0'^{jr} - V_0^{jr}\right) = \sum_{j=1}^{J}\left(\frac{L_0^{jr}}{L_0^r}\right)\log\left(\mathcal{E}^{jr}\right)$$

Landlords' Welfare The lifetime utility of a landlord, W_0^r, in region r is defined as the present discounted value of real consumption, where income comes from the land rents and the consumption share are given by the workers' decisions,

$$W_0^r = \sum_{t=0}^{\infty} \beta^t \log\left(\frac{q_t^r H^r}{P_t^r}\right), \quad P_t^r = \prod_{\tilde{j}=1}^{J}\left(p_t^{\tilde{j}r}\right)^{s_t^{\tilde{j}r}}.$$

Thus, I define the equivalent variation for a landlord as the scalar $\mathcal{R}^r$ that satisfies:

$$W_0'^r = W_0^r + \sum_{t=0}^{\infty} \beta^t \log\left(\mathcal{R}^r\right),$$

$$\log\left(\mathcal{R}^r\right) = (1-\beta)\sum_{t=0}^{\infty} \beta^t \log\left(\frac{q_t'^r / q_t^r}{P_t'^r / P_t^r}\right) = \sum_{t=1}^{\infty} \beta^t \log\left(\frac{\hat{q}_t^r}{\hat{P}_t^r}\right).$$

Figure 25 plots the spatial pattern and distribution function of welfare losses for landlords.

B.5 Migration Flows

To construct migration flows across more than 1,700 markets, where a market is identified as a sector-region combination, I extend the procedure outlined in Azose and Raftery (2019) as follows. To ease the exposition, define M_t^{br} as the number of persons born in region b and residing in r in period t.

First, I control for births and deaths to guarantee that changes in the migration stocks reflect movements across regions, rather than natural population changes. Data on births and deaths at the country- and

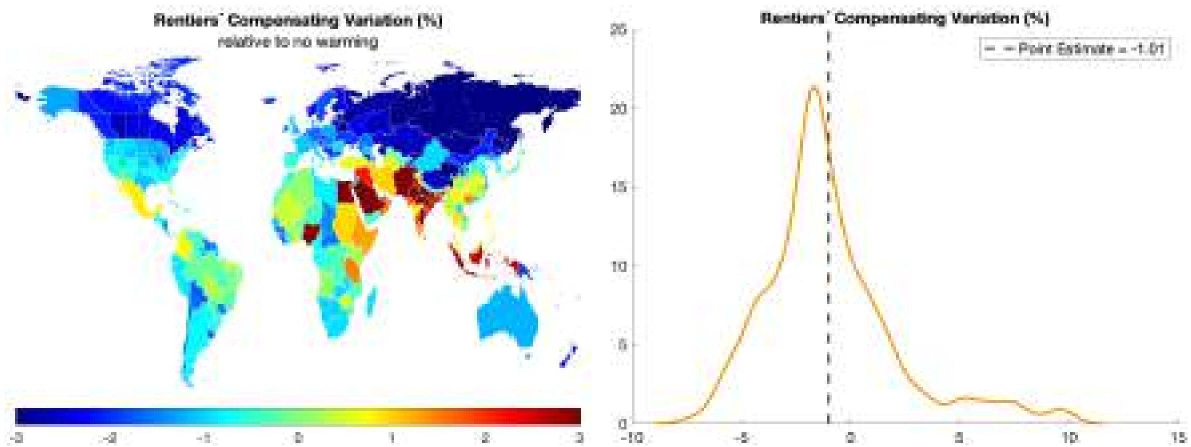

Figure 25: Average workers' and landlords' welfare losses due to global warming.

subnational-level is described in Appendix A.5.

The number of deaths in the time interval t to $t+1$ is subtracted from the stock data at time t. Since I only observe deaths by place of residence, $d^r_{t,t+1}$, and not its decomposition by place of residence and place of birth, I proportionally allocate the number of deaths to each population stock.

The number of births in the time interval t to $t+1$ is subtracted from the stock data at time $t+1$. Since I only observe births by place of residence, $b^r_{t,t+1}$, I assume that there is no migration of newborns, in other words, births are assumed to only affect the native born stock. Define the migration stocks that account for natural demographic changes with a prime,

$$M_t^{'br} = M_t^{br} - d^r_{t,t+1}(M_t^{br}/M_t^{+r}),$$
$$M_{t+1}^{'br} = M_{t+1}^{br} - b^r_{t,t+1}\mathbb{1}\{b = r\}.$$

After controlling for natural population changes, any difference in the number of persons born in a particular region in the time interval t to $t+1$ must reflect the migrant transitions to or from outside external regions.[65] When the difference between period $t+1$ minus t is greater than zero, $M'_{t+1}{}^{b+} - M_t'^{b+} > 0$, migrants have arrived from external regions. Conversely, a negative difference implies that migrants have moved away to external regions. Define the migration stocks that account for external migration with a double prime,

$$M_t^{''br} = M_t^{'br} - \sum_{b=1}^{R} \mathcal{W}_t^{br} \cdot |M_{t+1}^{'b+} - M_t^{'b+}| \cdot \mathbb{1}\{M_{t+1}^{'b+} - M_t^{'b+} < 0\}, \tag{B.14}$$

$$M_{t+1}^{''br} = M_{t+1}^{'br} - \sum_{b=1}^{R} \mathcal{W}_{t+1}^{br} \cdot |M_{t+1}^{'b+} - M_t^{'b+}| \cdot \mathbb{1}\{M_{t+1}^{'b+} - M_t^{'b+} > 0\}, \tag{B.15}$$

$$1 = \sum_{r=1}^{R} \mathcal{W}_t^{br} = \sum_{r=1}^{R} \mathcal{W}_{t+1}^{br} \tag{B.16}$$

and denote by $\mathcal{W}_t^{br}, \mathcal{W}_{t+1}^{br}$ the breakdown variables that allocate population across regions. I improve the

[65]Due to lack of information, the spatial coverage excludes a few countries of the world.

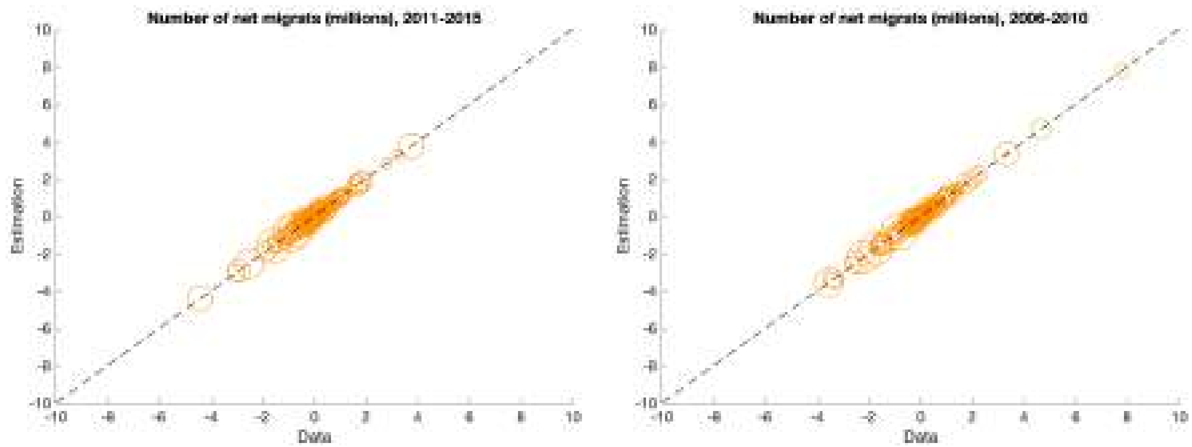

Figure 26: Comparison of net migration rates in the data and the estimation.

estimation of the breakdown parameters relative to Abel (2013) to target the net migration rates observed in the data between periods t and $t+1$, $N^r_{t,t+1}$. The model induced net migration rate in region r is defined as the difference between $M^{''+r}_{t+1}$ and $M^{''+r}_{t}$ relative to the average population over that period, $(M^{''+r}_{t} + M^{''+r}_{t+1})/2$,

$$\begin{aligned} \min_{\mathcal{W}} \quad & \sum_{r=1}^{R} \left(2\frac{M^{''+r}_{t+1} - M^{''+r}_{t}}{M^{''+r}_{t+1} + M^{''+r}_{t}} - N^r_{t,t+1} \right)^2 \\ \text{st} \quad & \text{(B.14), (B.15) and (B.16)} \\ & \mathcal{W}^{br}_t, \mathcal{W}^{br}_{t+1} \in [0,1]. \end{aligned}$$

Figure B.5 compares of net migration rates in the data and the estimation. After such adjustment, the changes in the migration stocks over two periods entirely reflect the movement of households across the regions of interest. To decompose migration stocks across working sectors, I assume that for each region of residence the share of households working in a particular sector does not depend on the birthplace,

$$M^{(jr)(b)}_t = (L^{jr}_t / L^{+r}_t) M^{''rb}_t.$$

Consequently, for each place of birth, I know the number of workers in each market jr from period t to period $t+1$. The next step is to estimate, for each place of birth, the mass of workers moving across markets.

Poisson regression models have been extensively used to represent migration models. I consider that the number of workers born in b moving from market jr to $j'r'$ follows a Poisson process with mean defined as follows,

$$m^{(jr)(j'r')(b)}_t = \beta^{(jr)}_{1,t} \cdot \beta^{(j'r')}_{2,t} \cdot \beta^{(r)(b)}_{3,t} \cdot \beta^{(r')(b)}_{4,t} \cdot \delta^{(r)(r')(b)}_{1,t} \cdot \delta^{(jr)(j'r')}_{2,t} \cdot \varpi^{(jr)(j'r')(b)}_t. \tag{B.17}$$

The coefficients $\beta^{(jr)}_{1,t}$ and $\beta^{(j'r')}_{2,t}$ account for the background characteristics of the market of origin and destination, respectively. The coefficients $\beta^{(r)(b)}_{3,t}$ and $\beta^{(r')(b)}_{4,t}$ account for the birthplace specific background characteristics of the region of origin and destination, respectively.

To allow for structural differences between migrants and stayers, equation (B.17) incorporates the dichotomic variables $\delta_{1,t}^{(r)(r')(b)} = \exp(\delta_{1,t}^{(r)(r)(b)} \cdot \mathbb{1}\{r = r'\})$ and $\delta_{2,t}^{(jr)(j'r')} = \exp(\delta_{2,t}^{(jr)(jr)} \cdot \mathbb{1}\{jr = j'r'\})$. The term $\varpi_t^{(jr)(j'r')(b)}$ represents an auxiliary information on migration flows, usually an inverse function of distance.[66]

The maximum log-likelihood estimates of the aforementioned parameters can be derived by considering the probability of observing $n_t^{(jr)(j'r')(b)}$, provided that migrant transitions are independent,

$$\begin{aligned}
\max_{\beta,\delta} \quad & \sum_{j=1}^{J}\sum_{j'=1}^{J}\sum_{r=1}^{R}\sum_{r'=1}^{R}\sum_{b=1}^{R}\left(n_t^{(jr)(j'r')(b)}\log\left(m_t^{(jr)(j'r')(b)}\right) - m_t^{(jr)(j'r')(b)} - \log\left(n_t^{(jr)(j'r')(b)}!\right)\right) \\
\text{st} \quad & (\text{B.17}).
\end{aligned}$$

I rearrange terms to arrive at the following problem, where the notation $+$ symbolizes the sum over the index of interest,

$$\begin{aligned}
\max_{\beta,\delta} \quad & \sum_{j=1}^{J}\sum_{r=1}^{R} n_t^{(jr)(++)(+)}\log\left(\beta_{1,t}^{(jr)}\right) + \sum_{j'=1}^{J}\sum_{r'=1}^{R} n_t^{(++)(j'r')(+)}\log\left(\beta_{2,t}^{(j'r')}\right) \\
& + \sum_{r=1}^{R}\sum_{b=1}^{R} n_t^{(+r)(++)(b)}\log\left(\beta_{3,t}^{(r)(b)}\right) + \sum_{r'=1}^{R}\sum_{b=1}^{R} n_t^{(++)(+r')(b)}\log\left(\beta_{4,t}^{(r')(b)}\right) \\
& + \sum_{r=1}^{R}\sum_{r'=1}^{R}\sum_{b=1}^{R} n_t^{(+r)(+r')(b)}\log\left(\delta_{1,t}^{(r)(r')(b)}\right) + \sum_{j=1}^{J}\sum_{j'=1}^{J}\sum_{r=1}^{R}\sum_{r'=1}^{R} n_t^{(jr)(j'r')(+)}\log\left(\delta_{2,t}^{(jr)(j'r')}\right).
\end{aligned}$$

The First Order Conditions of the Maximum Likelihood estimation are listed below. Since there is no closed-form solution for the parameters of interest, I iterate over the optimality until convergence,

$$\begin{aligned}
\beta_{1,t}^{(jr)}: \quad m_t^{(jr)(j'r')(b)} &= \left(\frac{n_t^{(jr)(++)(+)}}{m_t^{(jr)(++)(+)}}\right) m_t^{(jr)(j'r')(b)}, \\
\beta_{2,t}^{(j'r')}: \quad m_t^{(jr)(j'r')(b)} &= \left(\frac{n_t^{(++)(j'r')(+)}}{m_t^{(++)(j'r')(+)}}\right) m_t^{(jr)(j'r')(b)}, \\
\beta_{3,t}^{(r)(b)}: \quad m_t^{(jr)(j'r')(b)} &= \left(\frac{n_t^{(+r)(++)(b)}}{m_t^{(+r)(++)(b)}}\right) m_t^{(jr)(j'r')(b)}, \\
\beta_{4,t}^{(r')(b)}: \quad m_t^{(jr)(j'r')(b)} &= \left(\frac{n_t^{(++)(+r')(b)}}{m_t^{(++)(+r')(b)}}\right) m_t^{(jr)(j'r')(b)}, \\
\delta_{1,t}^{(r)(r')(b)}: \quad m_t^{(jr)(j'r')(b)} &= \left(\frac{n_t^{(+r)(+r')(b)}}{m_t^{(+r)(+r')(b)}}\right) m_t^{(jr)(j'r')(b)} \text{ if } r = r', \\
\delta_{2,t}^{(jr)(j'r')}: \quad m_t^{(jr)(j'r')(b)} &= \left(\frac{n_t^{(jr)(j'r')(+)}}{m_t^{(jr)(j'r')(+)}}\right) m_t^{(jr)(j'r')(b)} \text{ if } (jr) = (j'r').
\end{aligned}$$

The structural parametrization of the Poisson process is designed so that the estimation only requires information on the marginal totals, which are observable, and an assumption on the number of stayers. Following Abel and Sander (2014), I set the diagonal values to their highest possible value, which is the

[66]Since the results are largely stable across different specifications of this variable, I set it equal to one.

minimum number of workers across two periods of time,

$$n_t^{(+r)(+r)(b)} = \min\left\{M_t^{(+r)(b)}, M_{t+1}^{(+r)(b)}\right\},$$
$$n_t^{(jr)(jr)(+)} = \min\left\{M_t^{(jr)(+)}, M_{t+1}^{(jr)(+)}\right\}.$$

As the diagonal values represent the maximum number of stayers in each market, the estimated off-diagonal elements are the minimum migration flows required to match the changes in migration stocks. Azose and Raftery (2019) relax the assumption on minimal migration and repeat the estimation the estimation by ignoring the differences between migrants and stayers, that is, omitting the coefficients in equation (B.17). Finally, the migration flows are a weighted average of the estimates of minimum migration flows and those under the independence model, where the weight to the former estimates equals 0.87.[67] The resulting migration flows are displayed in Figures 27-35.

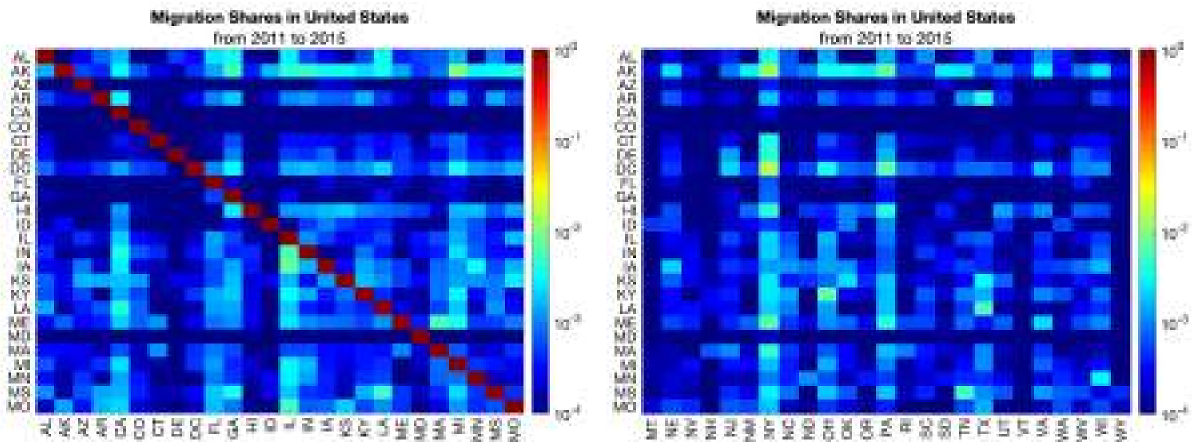

Figure 27: Migration shares across states in the United States in the period 2011-2015.

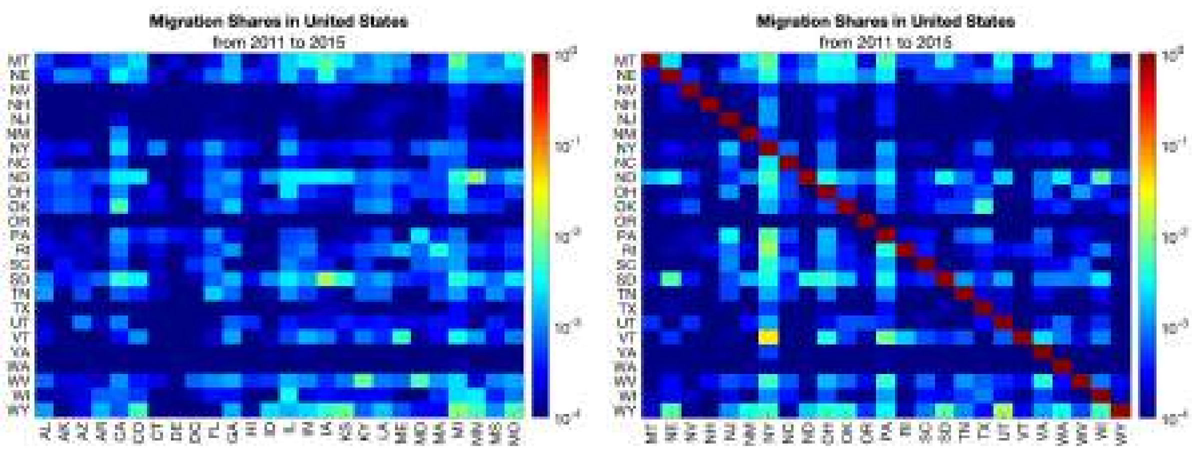

Figure 28: Migration shares across states in the United States in the period 2011-2015.

[67] Azose and Raftery (2019) find that this weight better replicates the migration flows constructed by the Integrated Modeling of European Migration (Raymer et al., 2013).

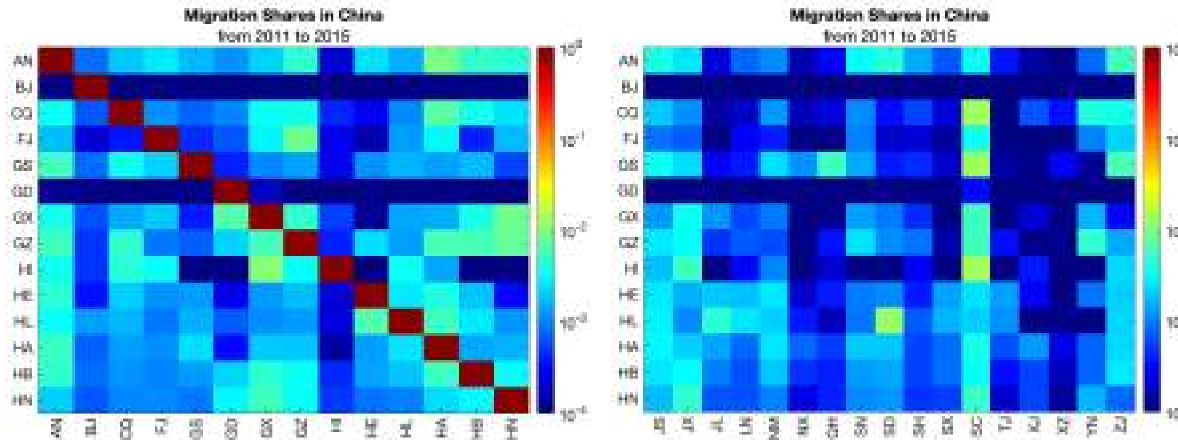

Figure 29: Migration shares across states in China in the period 2011-2015.

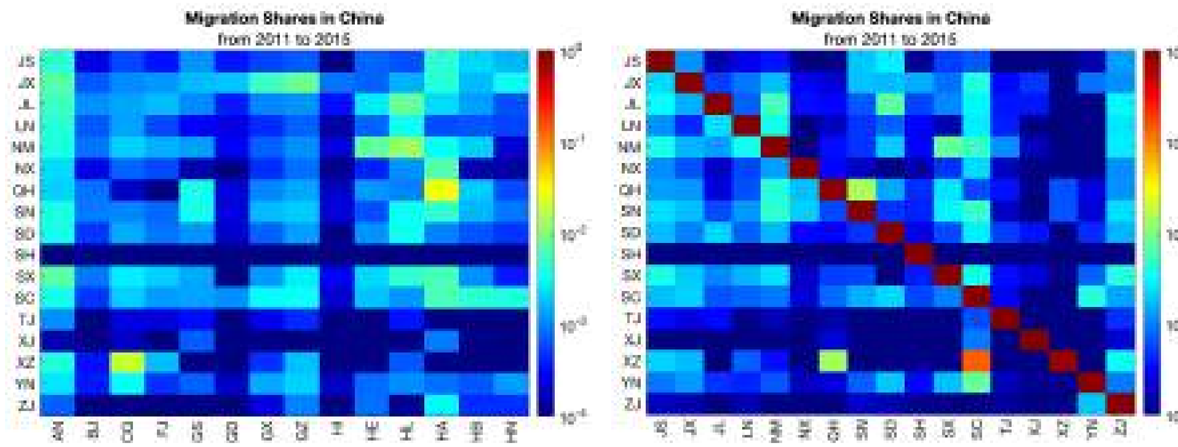

Figure 30: Migration shares across states in China in the period 2011-2015.

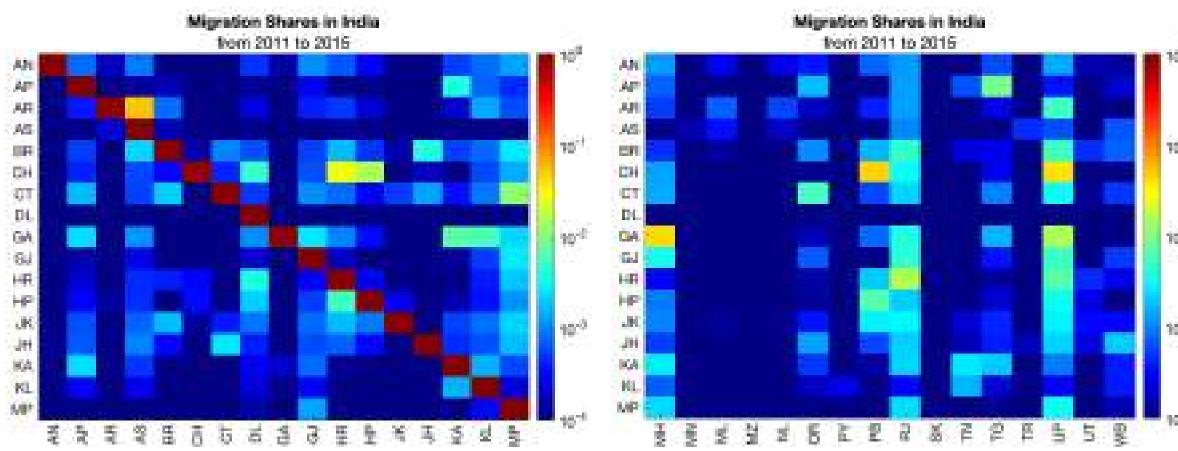

Figure 31: Migration shares across states in India in the period 2011-2015.

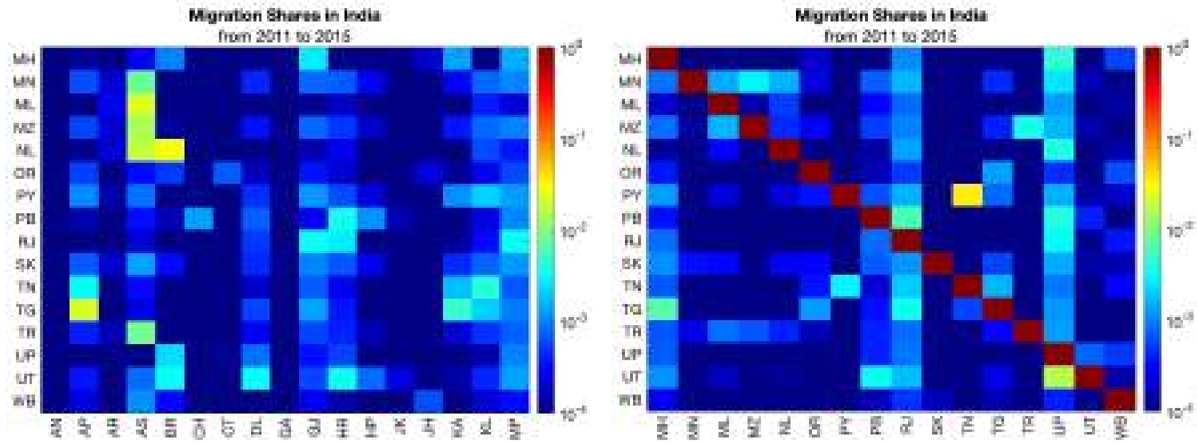

Figure 32: Migration shares across states in India in the period 2011-2015.

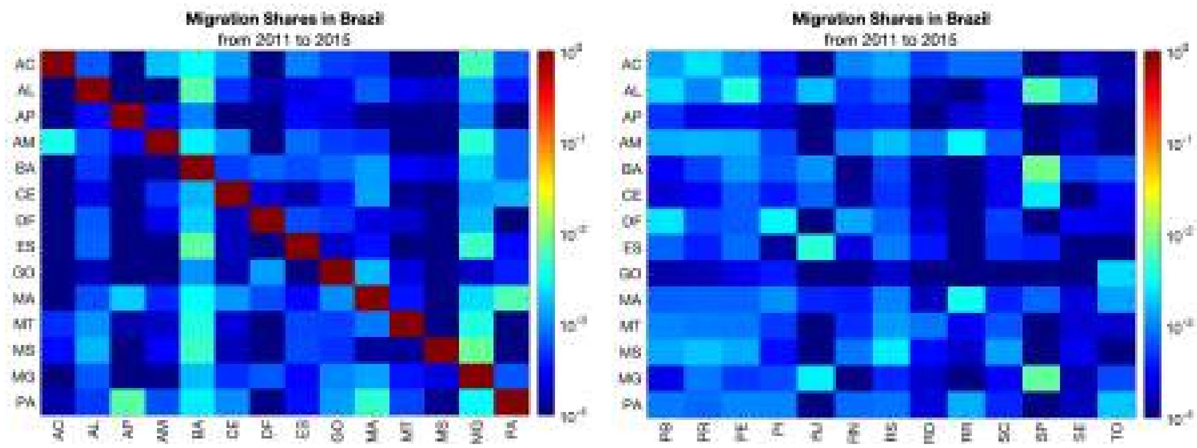

Figure 33: Migration shares across states in Brazil in the period 2011-2015.

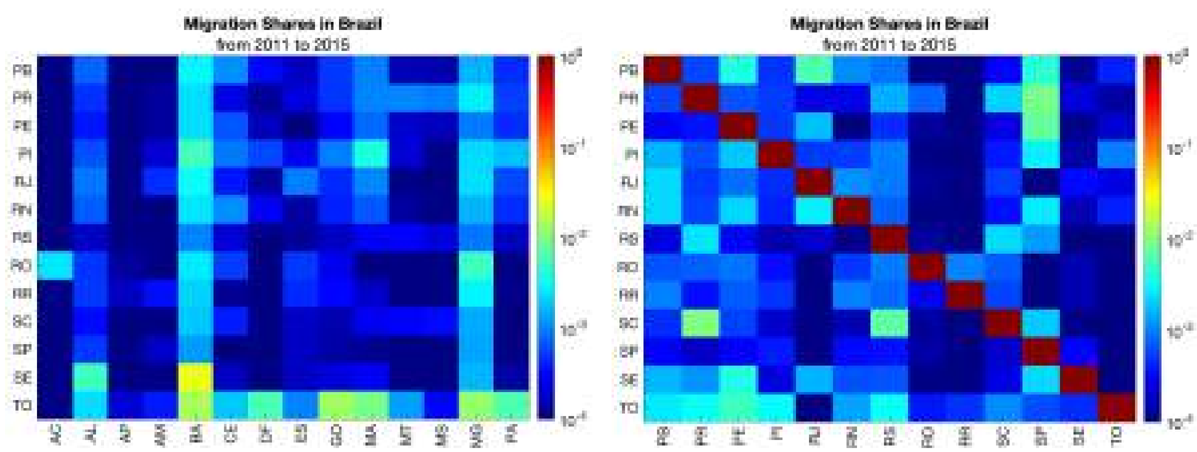

Figure 34: Migration shares across states in Brazil in the period 2011-2015.

B.6 Algorithm

Below I outline the algorithm to numerically implement the solution of the competitive equilibrium in time differences, conditional on an initial observable allocation $(w_0, L_0, E_0^f, E_0^c, \pi_0, \mu_{-1}, S_{1,0}, S_{2,0}, \Upsilon_0)$ and

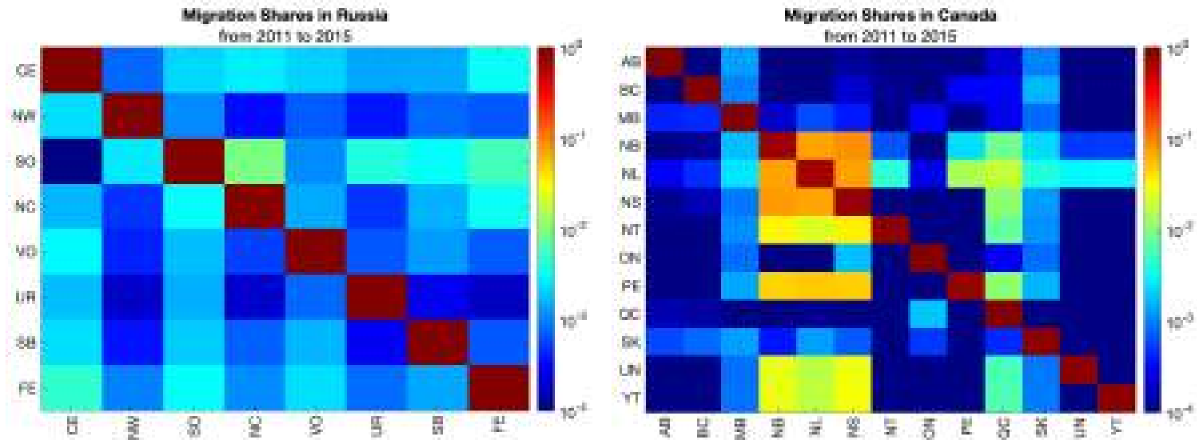

Figure 35: Migration shares across states in Canada and Russia in the period 2011-2015.

an environmental converging sequence for the exogenous fundamentals $\{\dot{\Theta}_{t+1}\}_{t=0}^{T}$.

(i) Guess a convergent path for the time differences of the value function transformation $\{\dot{v}_{t+1}^{(0)}\}_{t=0}^{T}$.

(ii) Guess a convergent path for the global evolution of carbon dioxide emissions $\{E_{t+1}^{f,(0)}\}_{t=0}^{T}$ and compute the path for local temperature $\{T_{t+1}^{r,(0)}\}_{t=0}^{T}$ and the evolution of productivity $\{\dot{\Omega}^{j}(T_{t+1}^{r,(0)})\}_{t=0}^{T}$.

(iii) For every period $t \geq 0$, use μ_{-1} and $\{\dot{v}_{t}^{(0)}\}_{t=0}^{T}$ to compute the migration shares $\{\mu_t\}_{t=0}^{T}$,

$$\mu_{t}^{(jr)(j'r')} = \frac{\mu_{t-1}^{(jr)(j'r')}\dot{\Xi}_{t}^{(jr)(j'r')}\left(\dot{v}_{t+1}^{j'r',(0)}\right)^{\beta}}{\sum_{\tilde{j}=1}^{J}\sum_{\tilde{r}=1}^{R}\mu_{t-1}^{(jr)(\tilde{j}\tilde{r})}\dot{\Xi}_{t}^{(jr)(\tilde{j}\tilde{r})}\left(\dot{v}_{t+1}^{\tilde{j}\tilde{r},(0)}\right)^{\beta}},$$

where $\Xi_{t}^{(jr)(j'r')} = \exp\left(\chi_{t}^{(jr)(j'r')}\right)^{-1/\nu}$.

(iv) For every period $t \geq 0$, use L_{0}^{jr} and $\{\mu_t\}_{t=0}^{T}$ to solve for $\{L_{t+1}\}_{t=0}^{T}$,

$$L_{t+1}^{j'r'} = \sum_{j=1}^{J}\sum_{r=1}^{R} L_{t}^{jr}\mu_{t}^{(jr)(j'r')}.$$

(v) For every period $t \geq 0$, solve the temporary equilibrium.

(a) Guess the global level of carbon dioxide emissions, $E_{t+1}^{f,(1)}$ and compute the time difference of the extraction cost, $\dot{h}(\dot{\Upsilon}_{t+1})$, and the time difference of the energy price, $\dot{p}_{t+1}^{e,jr}$.

(b) Given $\dot{L}_{t+1}^{jr}$, guess a value for the wages in time difference $\dot{w}_{t+1}^{jr,(0)}$.

(c) Compute the time difference of land rents and energy price,

$$\dot{q}_{t+1}^{r} = \sum_{j=1}^{J}\phi_{t}^{jr}\dot{w}_{t+1}^{jr,(0)}\dot{L}_{t+1}^{jr}, \qquad \phi_{t}^{jr} = \frac{w_{t}^{jr}L_{t}^{jr}}{\sum_{\tilde{j}=1}^{J}w_{t}^{\tilde{j}r}L_{t}^{\tilde{j}r}},$$

$$\dot{p}_{t+1}^{e,jr} = \left(\varrho_{t}^{jr}\left(\dot{p}_{t+1}^{f,jr}\right)^{1-\zeta} + (1-\varrho_{t}^{jr})\left(\dot{p}_{t+1}^{c,jr}\right)^{1-\zeta}\right)^{1/(1-\zeta)}, \qquad \varrho_{t}^{jr} = \frac{p_{t}^{f,jr}e_{t}^{f,jr}}{p_{t}^{jr}e_{t}^{jr}}.$$

(d) Solve for the time difference of input cost and the final good price,

$$\dot{\varkappa}^{jr}_{t+1} = \left(\left(\dot{w}^{jr}_{t+1}\right)^{\alpha^L} \left(\dot{q}^{r}_{t+1}\right)^{\alpha^H} \left(\dot{p}^{e,jr}_{t+1}\right)^{\alpha^E} \right)^{(1-\omega^{jr})/\alpha^W} \left(\prod_{\tilde{j}=1}^{J} \left(\dot{p}^{\tilde{j}r}_{t+1}\right)^{\omega^{(\tilde{j}r)(jr)}} \right)^{\omega^{jr}/\alpha^W},$$

$$\dot{p}^{jr}_{t+1} = \left(\sum_{\tilde{r}=1}^{R} \pi_t^{(j\tilde{r})(jr)} \left(\dot{\varkappa}^{j\tilde{r}}_{t+1} \dot{\kappa}^{(j\tilde{r})(jr)}_{t+1}\right)^{-\theta} \left(\dot{A}^{j\tilde{r}}_{t+1} \dot{\Omega}^{j} \left(T^{\tilde{r}}_{t+1}\right)\right)^{\theta(1-\omega^{j\tilde{r}})} \right)^{-1/\theta}.$$

(e) Calculate trade shares,

$$\pi_{t+1}^{(j\tilde{r})(jr)} = \pi_t^{(j\tilde{r})(jr)} \left(\dot{\varkappa}^{j\tilde{r}}_{t+1} \dot{\kappa}^{(j\tilde{r})(jr)}_{t+1}\right)^{-\theta} \left(\dot{A}^{j\tilde{r}}_{t+1} \dot{\Omega}^{j} \left(T^{\tilde{r}}_{t+1}\right)\right)^{\theta(1-\omega^{j\tilde{r}})} \left(\dot{p}^{jr}_{t+1}\right)^{-\theta}.$$

(f) Solve for the time difference of utility,

$$\dot{u}^{jr}_{t+1} = \frac{\left(\dot{w}^{jr,(0)}_{t+1}\right)^{1-\varsigma}}{\sum_{\tilde{j}=1}^{J} s_t^{(\tilde{j}r)(j)} \left(\dot{p}^{\tilde{j}r}_{t+1}\right)^{1-\varsigma} \left(\dot{u}^{jr}_{t+1}\right)^{\vartheta^{\tilde{j}}-1}}.$$

(g) Retrieve consumption shares,

$$s_{t+1}^{(\tilde{j}r)(j)} = s_t^{(\tilde{j}r)(j)} \left(\frac{\dot{p}^{\tilde{j}r}_{t+1}}{\dot{w}^{\tilde{j}r,(0)}_{t+1}}\right)^{1-\varsigma} \left(\dot{u}^{jr}_{t+1}\right)^{\vartheta^{\tilde{j}}}.$$

(h) Solve for expenditures,

$$X^{jr}_{t+1} = \sum_{\tilde{j}=1}^{J} s_{t+1}^{(\tilde{j}r)(j)} \dot{w}^{\tilde{j}r,(0)}_{t+1} w^{\tilde{j}r}_t \dot{L}^{\tilde{j}r}_{t+1} L^{\tilde{j}r}_t + s_{t+1}^{(jr)} \sum_{\tilde{j}=1}^{J} (\alpha^H/\alpha^L) \dot{w}^{\tilde{j}r,(0)}_{t+1} w^{\tilde{j}r}_t \dot{L}^{\tilde{j}r}_{t+1} L^{\tilde{j}r}_t$$
$$+ \sum_{\tilde{j}=1}^{J} \frac{\omega^{(jr)(\tilde{j}r)}}{1-\alpha^E(1-\omega^{\tilde{j}r})} \sum_{\tilde{r}=1}^{R} \pi_{t+1}^{(\tilde{j}r)(\tilde{j}\tilde{r})} X^{\tilde{j}\tilde{r}}_{t+1}.$$

(i) Retrieve the time difference of wages,

$$\dot{w}^{jr,(1)}_{t+1} w^{jr}_{t+1} \dot{L}^{jr}_{t+1} L^{jr}_t = \left(\alpha^L/\alpha^W\right) \left(1-\omega^{jr}\right) \left(\sum_{\tilde{r}=1}^{R} \pi_{t+1}^{(jr)(j\tilde{r})} X^{j\tilde{r}}_{t+1} \right).$$

If the difference between the guess and the solution of the time difference of wages is lower than a certain tolerance, go to the next step. Otherwise, return to step (vb) and iterate until convergence.

(j) Retrieve the time difference of use of fossil fuels and clean energy,

$$\dot{p}^{f,jr}_{t+1} \dot{e}^{f,jr,(1)}_{t+1} = \dot{w}^{jr,(1)}_{t+1} \dot{L}^{jr}_{t+1} \left(\frac{\dot{p}^{f,jr}_{t+1}}{\dot{p}^{e,jr}_{t+1}}\right)^{1-\zeta}, \qquad \dot{p}^{c,jr}_{t+1} \dot{e}^{c,jr,(1)}_{t+1} = \dot{w}^{jr,(1)}_{t+1} \dot{L}^{jr}_{t+1} \left(\frac{\dot{p}^{c,jr}_{t+1}}{\dot{p}^{e,jr}_{t+1}}\right)^{1-\zeta},$$

$$E^{f,(1)}_{t+1} = \sum_{j=1}^{J} \sum_{r=1}^{R} \dot{e}^{f,jr,(1)}_{t+1} \dot{e}^{f,jr}_t.$$

If the difference between the guess and the solution of the carbon dioxide emissions is lower than a certain tolerance, go to the next step. Otherwise, return to step (va) and iterate until convergence.

(vi) If the difference between $\{E_{t+1}^{f,(0)}\}_{t=0}^{T}$ and $\{E_{t+1}^{f,(1)}\}_{t=0}^{T}$ is lower than a certain tolerance, go to the next step. Otherwise, return to step (ii), update the evolution of productivity, $\{\dot{\Omega}^{j}(T_{t+1}^{r,(1)})\}_{t=0}^{T}$, and iterate until convergence.

(vii) For every period $t \geq 0$, use the solution of the temporary equilibrium to solve backwards for $\{v_t^{(1)}\}_{t=0}^{T}$,

$$\dot{v}_t^{jr,(1)} = \left(\dot{B}_t^{jr}\dot{u}_t^{jr}\right)^{1/\nu}\left(\sum_{j'=1}^{J}\sum_{r'=1}^{R}\mu_{t-1}^{(jr)(j'r')}\left(\dot{v}_{t+1}^{j'r',(0)}\right)^{\beta}\right).$$

If the difference between $\{\dot{v}_{t+1}^{(0)}\}_{t=0}^{T}$ and $\{\dot{v}_{t+1}^{(1)}\}_{t=0}^{T}$ is lower than a certain tolerance, the algorithm concludes. Otherwise, return to step (i).