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ESSAYS ON ECONOMIC GEOGRAPHY AND PLACE-BASED POLICIES

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ABSTRACT

This dissertation contributes to the literature on place-based policies, studying how regional externalities and spatial linkages should shape policy design. I show that the nature of agglomeration externalities and the general equilibrium forces of trade and migration are central to understanding both the optimal design of industrial policy and the distribution of climate risk across regions.

The first chapter builds on the fact that advanced economies like the US, UK, and European Union have spent billions subsidizing specific industries heterogeneously across regions, yet the optimal design of such place-based industrial policies remains unclear. I provide a theoretical framework to address this. I show that the optimal policy depends on the underlying productivity structure: whether agglomeration affects Hicks-neutral or Harrod-neutral productivity, the two dominant formulations in spatial economics. When productivity is Hicks-neutral, optimal subsidies increase with regional sector size, supporting place-based targeting; when Harrod-neutral, a uniform subsidy is optimal. Applying this framework to manufacturing in England, I find predominantly Hicks-neutral technology, supporting place-based over uniform policies

The second chapter analyzes how nonlinear damages and the general equilibrium forces of trade and migration filter climate risk across time and space. Leveraging a dynamic spatial model linking countries through trade and migration, I derive analytical first- and second-order welfare approximations that decompose the mean and variance of welfare changes into damage function, trade, and migration components. Using an ensemble of temperature projections from CMIP-6 and an empirically estimated damage function, I show that climate change-induced welfare risk is large: the standard deviation of country-level projected welfare loss is on average over 8% — compared to an average welfare loss of 13% — and is spatially unequal. Spatial linkages reshape not only the level of climate damages but also their distribution: accounting for trade and migration can reduce the standard deviation of welfare changes by up to 40% in low-income, internationally integrated nations.

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Chapter 1

Technology and the Geography of Industrial Policy

Abstract

Industrial policy around the world is increasingly targeting sectors heterogeneously across regions to account for sectoral agglomeration externalities. This paper provides a theoretical framework to study when such spatial targeting is optimal. I demonstrate that the optimal policy across regions depends on the underlying productivity structure: whether agglomeration affects Hicks-neutral (input-neutral) or Harrod-neutral (labor-augmenting) productivity, the two dominant formulations in spatial economics. When productivity is Hicks-neutral, optimal industrial subsidies increase with regional sector size. However, when productivity is Harrod-neutral, optimal industrial policy is a constant ad-valorem wage subsidy across all regions. I apply this framework to manufacturing in England using data on 153 regions, where I estimate the productivity structure and the agglomeration elasticity. In the Hicks-neutral case, place-based policies raise welfare by 5.1% versus 2% for uniform subsidies. In the Harrod-neutral case, uniform subsidies raise welfare by 3.1%, while place-based ones reduce welfare by 0.7%. The estimation reveals predominantly Hicks-neutral technology, supporting place-based over uniform policies for manufacturing in England.

1.1 Introduction

Industrial policy is experiencing a dramatic global resurgence. There were over 2,500 industrial policy interventions across the world in 2023 alone, compared to fewer than 200 in 2010 (IMF Staff, 2024, World Bank, 2024). What makes this wave particularly noteworthy is its spatial dimension: a substantial share of these policies offer heterogeneous subsidies across regions for a given sector. These policies represent a departure from traditional industrial policy which would provide uniform support to sectors across regions. The underlying rationale is that agglomeration externalities operate at a region-sector level creating location specific industrial spillovers (Brülhart and Mathys, 2008, Greenstone et al., 2010) that build a case for spatially differentiated interventions. Policymakers argue that place-based targeting can better exploit these localized spillovers to generate industrial clusters and achieve superior welfare outcomes.[1]

This shift toward place-based industrial policies (PBIPs) spans economies worldwide, representing billions of dollars in spatially-targeted spending. In the United States, recent legislation including the Inflation Reduction Act, CHIPS and Science Act, American Rescue Plan Act, and Bipartisan Infrastructure Law have allocated nearly $40 billion from 2021-2024 specifically on account of PBIPs (Brookings Institution, 2024). The European Union's €45 billion REPowerEU plan and Net-Zero Industry Act explicitly target regional manufacturing capacity, aiming for 40% domestic production of strategic clean technologies by 2030. Similarly, Australia's Future Made in Australia program commits A$22.7 billion to place-based workforce transitions and clean energy manufacturing zones. The UK's recently released 10 year industrial strategy, Invest 2035, explicitly emphasizes policy to foster industrial clusters across eight targeted sectors, with particular focus on exploiting regional comparative advantages. These represent only a few examples from around the world.

Yet this policy momentum has outpaced economic analysis. Duranton (2011) and Nathan

[1] See Neumark and Simpson (2015), subsection 18.2.3, for a summary of this argument.

and Overman (2013) argue that cluster based industrial policies rest on weak theoretical foundations and limited empirical support. While economists understand that region-sector agglomeration externalities create potential market failures, the optimal design of corrective industrial policies in the presence of these externalities remains unclear. A few fundamental questions emerge: When should industrial policy target regions heterogeneously? If place-based industrial policies are indeed optimal, what dictates our choice of regions and the consequent distribution of subsidies? What are the welfare gains from a place-based industrial policy relative to traditional place-neutral industrial policy?

The central contribution of this paper is to show that while region-sector agglomeration externalities are necessary to conduct place-based industrial policies, they are not sufficient. Optimal industrial policy design depends critically on the underlying productivity structure. Specifically, whether productivity is Hicks-neutral (factor-neutral) or Harrod-neutral (labor-augmenting), which are the two dominantly assumed structures in spatial economics. I show that the optimal industrial policy entails a per-worker subsidy to the targeted sector which varies across regions when externalities affect Hicks-neutral productivity. In contrast, when externalities affect Harrod-neutral productivity, the optimal industrial policy is a constant ad-valorem wage subsidy to the targeted sector across all regions. I estimate the productivity structure for the manufacturing sector in England, where I find predominantly Hicks-neutral technology suggesting that place-based subsidies outperform uniform subsidies.

The distinction between Hicks-neutral and Harrod-neutral productivities has deep roots in economic analysis. This classification is important to consider since it captures fundamentally different ways that productivity improvements affect the production process. Hicks-neutral progress increases the productivity of all factors proportionally, while Harrod-neutral progress specifically augments labor productivity, leaving the marginal productivity of other factors unchanged.[2] This distinction has proven central to a multitude of literatures

[2]Another widely used form of technological progress in the endogeneous growth literature is that of Solow-neutral or capital-augmenting growth. I abstract away from this since there is little evidence to suggest agglomeration externalities like the ones I consider affect only capital.

including endogenous growth theory, where the productivity structure determines both the sources and sustainability of economic growth, as well as directed technical change where the bias of technological growth has implications for macroeconomic aggregates.[3]

In the context of agglomeration, this distinction is particularly important for policy design. Existing empirical and theoretical work on agglomeration typically adopts a specific assumption—either factor-neutral or labor-augmenting productivity. However, the empirical accuracy of these assumptions and their implications for policy design remain largely unexplored. This paper demonstrates that distinguishing between these two mechanisms is essential for deriving optimal policy and proposes a methodology to estimate the underlying productivity structure.

The theoretical foundation for people as sources of agglomeration externalities traces back to at least Marshall (1890), who observed how workers in concentrated industries benefit from proximity through knowledge sharing and learning. This insight continues to influence agglomeration theory and explanations of urban economic growth (Jacobs, 1969, Lucas Jr, 1988). Duranton and Puga (2004) provide a comprehensive review of these mechanisms.

The detailed quantitative analysis of the questions posed by this paper requires a number of contributions that fall along four main dimensions.

First, I develop a spatial equilibrium model featuring multiple regions and sectors, with agglomeration externalities operating at the region-sector level. A crucial feature is to allow the productivity structure to vary continuously from completely Harrod-neutral (labor-augmenting) to completely Hicks-neutral (factor-neutral). I capture this distinction with a productivity structure parameter $\iota \in [0, 1]$. As ι goes from 0 to 1, the productivity structure moves from purely Harrod-neutral to purely Hicks-neutral. Regions differ in trade costs, base productivities, land endowments, and amenities, creating heterogeneous industrial composition across regions that affects optimal policy design. Workers choose locations subject to idiosyncratic preferences, generating realistic regional population distributions. This frame-

[3]See Acemoglu (2008) for a review.

work is rich enough to capture the essential economic mechanisms that determine the spatial distribution of economic activity while remaining tractable for empirical analysis.

Second, I solve for efficient allocations in this setting across all productivity structures.[4] The key insight is that the region-sector externality creates a misallocation of workers across sectors within each region, and that has implications for the broader spatial distribution of economic activity. Crucially, the productivity structure directly affects how policy instruments should be designed to account for the inefficiency in the decentralized allocation. I then decentralize the efficient allocation using specific policy instruments.

When externalities affect Hicks-neutral productivity, optimal industrial policy requires region specific subsidies per worker in the targeted sector. The subsidy size scales with the underlying revenue per worker in each location implying greater support to the biggest regions for any given sector. The economic intuition is that under Hicks-neutral production, externalities from an additional worker benefit all factors of production, with the total value of the externality captured by revenue per worker. These subsidies are heterogeneous across space even when the agglomeration parameters are identical across regions and/or sectors.[5] Spatial variation in sector size, despite uniform agglomeration elasticities, creates the economic case for place-based targeting that explicitly favors regions with larger sectoral bases.

This contrasts with the case when externalities affect Harrod-neutral productivity. Here, the optimal industrial policy is a uniform ad-valorem wage subsidy to the targeted sector across all regions since externalities from additional workers affect only labor productivity. Since competitive wages already capture the marginal value of workers in all regions, policy

[4]This analysis focuses on efficiency maximizing industrial policy design, abstracting from distributional, national security, geopolitical, or any other considerations. This approach aligns with a substantial portion of real world industrial policy interventions: Evenett et al. (2024) find that competitiveness and economic efficiency motivations account for more than a third of all industrial policy measures in 2023, representing the most commonly stated objective for government intervention.

[5]I focus on the case with constant agglomeration externalities across regions since the literature has not found substantial evidence suggesting variation in the agglomeration elasticity across regions. Few studies have been able to estimate the parameter across regions due to the data requirements. See Combes and Gobillon (2015) for a review.

directly targets them through wage subsidies proportional to the strength of agglomeration.

Third, I develop a strategy to estimate the productivity structure parameter ι and the manufacturing agglomeration externality ϕ_m at a region-sector level using data across 153 regions in England for the manufacturing sector. I exploit historical variation in Polish settlement patterns to instrument for manufacturing employment. I can estimate a reduced form elasticity using model implied factor demand for firms that depends on both ι and ϕ_m. Separately, inverting the model to recover regional productivities allows me to estimate ϕ_m—but these productivities themselves depend on the value of ι. This establishes two nonlinear equations in $\{\iota, \phi_m\}$ which I can solve to obtain a unique estimate for both. In the case of English manufacturing, I estimate $\iota^* = 0.906$ which means predominantly Hicks-neutral production, implying that place-based policies should dominate uniform alternatives.

Fourth, I quantify the welfare gains from place-based industrial policy for manufacturing in England and analyze the spatial distribution of optimal subsidies. At the estimated productivity structure $\iota^* = 0.906$, the optimal industrial policy mix increases welfare by 4.8%. The place-based subsidies target revenue per worker: regions in the Midlands and North receive the highest per-worker subsidies, while southern regions closer to London receive substantially lower subsidies. I also examine constrained policy designs to assess whether more realistic policy designs can capture most of the first best welfare gains.

Finally, for robustness, I contrast welfare gains from place-based as well as uniform industrial policy by solving the model across a range of productivity structures to further inform policy choice under parameter uncertainty. Place-based policies generate gains of 5.1% compared to 2.0% from uniform wage subsidies when externalities affect Hicks-neutral productivity ($\iota = 1$). When externalities affect Harrod-neutral productivity ($\iota = 0$), uniform wage subsidies increase welfare by 3.1% while place-based policies actually reduce welfare by 0.7%.

This variation in welfare implications for a given policy reveals important downside risks from policy misdesign. PBIPs do not universally increase welfare. They only target the cor-

rect externality when production is predominantly Hicks-neutral. The welfare consequences of PBIPs exhibit high variance across productivity structures, with it being potentially harmful under Harrod-neutral production. The subsidies implied by the PBIPs exceed the size of the externality and cause an 'over correction'. Conversely, uniform wage subsidies deliver stable welfare gains across all productivity structures, never reducing welfare below the no-policy baseline. This stability reflects that wage subsidies target labor's marginal product, which is always less than revenue per worker, providing a natural safeguard against over subsidization.

These results imply that identifying how productivity externalities enter production is central to the design of optimal industrial policy. It is of paramount importance to estimate the productivity structure parameter in order to determine how industrial subsidies should be distributed. Yet this parameter has largely been overlooked in the literature. By showing that different productivity structures imply fundamentally different optimal policies, this paper highlights the importance of estimating this dimension of production.

Relation to the literature: This paper contributes to the growing literature exploring spatial misallocation and the role of place-based policies. Early theoretical work questioned the rationale for place-based policies. Glaeser and Gottlieb (2008) and Kline and Moretti (2014) argue that with constant elasticity spillovers across space and no possibility for transfers, place-based policies cannot improve upon market outcomes. Fajgelbaum and Gaubert (2020) break this assumption and show how cross-regional transfers can improve welfare despite constant spillovers. They also show how the presence of externalities across worker types creates a role for place-based transfers. Rossi-Hansberg et al. (2025) generalize this framework by allowing externalities to depend not only on the number of different worker types in a region but also their relative composition.

A broader literature studies spatial policy in contexts such as infrastructure and traffic (Fajgelbaum and Schaal, 2020; Allen and Arkolakis, 2022; Bordeu, 2025; Hierons, 2025), capital allocation (Irissari, 2025), taxation (Albouy, 2009; Fajgelbaum et al., 2019; Colas

and Hutchinson, 2021), regional competition (Ferrari and Ossa, 2023), zoning and housing (Herkenhoff et al., 2018; Hsieh and Moretti, 2019), industrial and economic zones (Farole, 2011; Busso et al., 2013; Briant et al., 2015; Alder et al., 2016; Wheeler, 2022), coordination failures (Owens III et al., 2020; Monte et al., 2023), climate policy (Conte et al., 2025), and redistribution (Gaubert et al., 2021). This paper contributes to this literature by exploring how region-sector agglomeration externalities in each region cause a misallocation of workers within and across regions which has implications for the overall distribution of economic activity. It further studies how the underlying productivity structure impacts the choice of optimal instruments, a mechanism that is largely overlooked in the existing literature.

The two most closely related papers are Fajgelbaum and Gaubert (2020) and Rossi-Hansberg et al. (2025). Both of these papers allow for multiple sectors, however the main externality they consider is that of agglomeration at a city level and cross externalities (across worker types). Rossi-Hansberg et al. (2021) extend this framework to discuss how occupations can dictate sectoral composition across regions in the US, given underlying characteristics in determining industrial productivity. However, these frameworks do not feature agglomeration effects at a sectoral level beyond the effects of occupational composition on sectors, and as such cannot discuss the role for industrial policy which explicitly targets sectors instead of occupations. The key implication of this is that there is a role for place-based policies without cross regional transfers or multiple worker types. Further, quite importantly, both these papers feature purely Harrod-neutral productivity (labor augmenting). I generalize the environment to consider all possible forms of productivity structures to see how this distinction impacts optimal spatial policy.

A second related strand examines the rationale and design of industrial policy, tracing back to classic arguments about externalities and coordination failures (Pigou, 1920; Rosenstein-Rodan, 1943; Murphy et al., 1989). Modern research evaluates industrial policies empirically (Criscuolo et al., 2019; Barwick et al., 2025; Lane, 2025) and, in the spatial context, place-based industrial programs (Mitrunen, 2020; LaPoint and Sakabe, 2021; Ata-

lay et al., 2023; Incoronato and Lattanzio, 2024; Garin and Rothbaum, 2025). Theoretical contributions incorporate international trade (Costinot et al., 2015; Costinot et al., 2020; Lashkaripour and Lugovskyy, 2023; Bartelme et al., 2025), financial frictions (Midrigan and Xu, 2014; Itskhoki and Moll, 2019), innovation (Akcigit et al., 2022), production networks (Liu, 2019), coordination failures (Sturm, 2023; Garg, 2025), climate policy (Acemoglu et al., 2016; Hahn et al., 2024; Gerarden et al., 2025), and political economy (Juhász and Lane, 2024), with comprehensive reviews provided in Juhász and Steinwender (2023) and Juhász et al. (2024).

My contribution to this literature is to explicitly incorporate the forces of economic geography into industrial policy design. I model how agglomeration externalities create endogenous variation in the returns to industrial policy across regions. This spatial perspective provides new insight into when and where governments should target industrial development, emphasizing that optimal policy design depends critically on both the productivity structure of targeted industries and the spatial distribution of economic activity.

Finally, this paper contributes to the literature emphasizing differences between productivity structures. A large macro literature emphasizes that the form of technological progress is central for understanding aggregate allocations: balanced-growth arguments imply that only Harrod-neutral progress is consistent with stable factor shares (Uzawa, 1961), and empirical work shows that imposing Hicks-neutral TFP can distort predictions of specialization and welfare in trade models (Gundlach, 2007). A parallel micro literature focuses on identifying technological bias from firms' input choices, with Doraszelski and Jaumandreu (2018) structurally estimating Hicks-neutral and labor-augmenting productivity using input-mix responses, and Rubens et al. (2024) showing that assuming the wrong bias can dramatically alter inferred labor-market distortions. Building on these insights, my paper develops an estimation strategy extending Doraszelski and Jaumandreu (2018) to an environment where productivity itself is endogenous to employment through agglomeration forces. I show that misidentifying the underlying technology systematically biases region-sector productivity

measurement and leads to large errors in the design of optimal place-based industrial policy.

The rest of this paper is organized as follows. Section 1.2 presents the multi-sector spatial model with a flexible productivity structure. Section 1.3 presents the theoretical results on efficient allocations, and the role for industrial policy. Section 1.4 introduces the quantitative setting and details the estimation strategy. Section 1.5 presents the results from different industrial policy counterfactuals. Section 1.6 presents a few model extensions and how results evolve with these. Section 1.7 concludes. I relegate many of the model's and quantification's details, and additional robustness exercises to the Appendix.

1.2 Quantitative model

An economy comprises N discrete regions indexed by $\{i, j\} \in \{1, \ldots, N\}$ and there are $K > 1$ discrete sectors indexed by $k \in \{1, \ldots, K\}$. In a given region, workers choose how much of each good to consume for each region-sector pair subject to iceberg trading costs $\tau_{ij} = \tau_{ji} \geq 1$. The economy as a whole is populated by a measure $\bar{L}$ of workers, each of whom is endowed with one unit of labor that is supplied inelastically. Workers choose where to live and work subject to preference shocks. For land, I follow the structure in Monte et al. (2018). I assume that each region is endowed with fixed land $\bar{H}_i$ which is owned by immobile landlords who use rental income to consume goods where they live.

1.2.1 Technology and Firms

There is an underlying region-sector specific productivity z_{ik} which is subject to an agglomeration externality in the amount of workers employed in the sector. Namely,

$$z_{ik} = \bar{z}_{ik} L_{ik}^{\phi_k}, \tag{1.1}$$

where $\bar{z}_{ik}$ is the underlying fundamental level of productivity. This defines a constant elasticity agglomeration externality for each sector governed by the parameter ϕ_k. In Section

1.6, I allow for the region-sector productivity to also depend on total region size L_i alongside L_{ik}.

Firm level production. Each region-sector consists of a continuum of identical, perfectly competitive firms. An individual firm ω in region-sector $\{i, k\}$ produces output using a CRS production function over labor and land,

$$q_{ik}(\omega) = z_{ik}^{\iota} f_k\left(z_{ik}^{1-\iota}\ell_{ik}(\omega), h_{ik}(\omega)\right),$$

where $\ell_{ik}(\omega)$ and $h_{ik}(\omega)$ denote the firm's employment and land use.[6] This formulation is general enough to embed both Hicks-neutral and Harrod-neutral productivity structures, parameterized by $\iota \in [0, 1]$:

1. For $\iota = 0$, production is Harrod-neutral:

$$q_{ik}(\omega) = f_k\left(z_{ik}\ell_{ik}(\omega), h_{ik}(\omega)\right).$$

   Productivity changes only impact the effective units of labor.

2. For $\iota = 1$, production is Hicks-neutral:

$$q_{ik}(\omega) = z_{ik} f_k\left(\ell_{ik}(\omega), h_{ik}(\omega)\right).$$

   Productivity changes impact all factors of production proportionally.

For $\iota \in (0, 1)$, we are in an intermediate case with productivity entering in both forms. The value of ι then determines if productivity is predominantly Harrod-neutral or Hicks-neutral. As such, ι is a critical parameter which is informative about how the agglomeration externalities impact production for each region-sector.

[6] I can relax this assumption to allow for more factors of production such as mobile capital or intermediate inputs, among others. We just need to ensure there are multiple factors of production in a CRS production function. In the presence of only one factor, the distinction between Hicks and Harrod-neutral production becomes a moot point.

Each firm takes productivity z_{ik}, wages w_i, land rents r_i, and output prices p_{ik} as given, and solves,

$$\max_{\ell_{ik}(\omega), h_{ik}(\omega)} \; p_{ik} z_{ik}^{\iota} f_k\left(z_{ik}^{1-\iota}\ell_{ik}(\omega), h_{ik}(\omega)\right) - w_i \ell_{ik}(\omega) - r_i h_{ik}(\omega).$$

Firms do not internalize the impact of their hiring decisions on aggregate productivity z_{ik}. Optimal factor demands satisfy

$$p_{ik} z_{ik} f'_{k,1} = w_i$$
$$p_{ik} z_{ik}^{\iota} f'_{k,2} = r_i.$$

Sector level aggregation. Because all firms within a region-sector are identical and face the same factor prices, they make identical factor demand choices. With CRS production and perfect competition, I can aggregate firm level decisions to the sector level without loss of generality. Define sector level aggregates as $L_{ik} = \int \ell_{ik}(\omega) d\omega$, $H_{ik} = \int h_{ik}(\omega) d\omega$, and $q_{ik} = \int q_{ik}(\omega) d\omega$. As such, sector level output can be represented as

$$q_{ik} = z_{ik}^{\iota} f_k\left(z_{ik}^{1-\iota} L_{ik}, H_{ik}\right).$$

In what follows, I work directly with these sector level quantities. Since factors of production are freely mobile across sectors within region, the factor prices must equalize. The condition for allocation of workers and land across sectors then becomes

$$p_{ik} z_{ik} f'_{k,1} = w_i = p_{ik'} z_{ik'} f'_{k',1} \qquad \forall k, k' \tag{1.2}$$
$$p_{ik} z_{ik}^{\iota} f'_{k,2} = r_i = p_{ik'} z_{ik'}^{\iota} f'_{k',2} \qquad \forall k, k'. \tag{1.3}$$

With free entry and perfect competition, price equals marginal cost. So,

$$p_{ik} = c_k(w_i, r_i, z_{ik}) \quad \forall k, i, \tag{1.4}$$

where $c_k(\cdot)$ is the marginal cost function for sector k which depends on the production function.

1.2.2 Workers and Consumption

Individual consumption and utility. Consider a worker living in region i. The worker has preferences over goods produced in each region-sector pair, represented by a consumption aggregator:

$$c_i = g\left(\{c_{i,jk}\}_{j,k=1}^{N,K}\right),$$

where $g(\cdot)$ is strictly concave in all goods.[7] Utility is iso-elastic in regional amenities a_i.[8] A worker, conditional on being in region i, solves

$$\max_{c_{i,jk}} u_i = a_i c_i$$
$$\text{subject to } \sum_{j}^{N}\sum_{k}^{K}\left(\tau_{ji} p_{jk}\right) c_{i,jk} = w_i.$$

I allow for an iso-elastic congestion externality through amenities. So,

$$a_i = \bar{a}_i L_i^{-\theta}, \tag{1.5}$$

[7]This structure ensures all industries have interior solutions in each region, ruling out analysis of policies targeting new industries or "infant industry" strategies. However, this accommodates most industrial policies in practice, as Juhász et al., 2022 find that industrial policy tends to target sectors where countries have revealed comparative advantage.

[8]This is standard in spatial models. Alternatively, amenities could enter additively: $u_i = c_i + a_i$. This does not affect optimal industrial policy results but influences cross regional transfers. See Donald et al. (2025) for details.

where $\theta \geq 0$ governs congestion strength. Optimal consumption equates marginal utility $\frac{\partial u_i}{\partial c_{i,jk}} = u'_{c_{i,jk}}$ with the trade cost adjusted price:

$$u'_{c_{i,jk}} = \tau_{ji} p_{jk} \quad \forall\ k, j. \tag{1.6}$$

This yields indirect utility as a function of amenities, wages, and the local price index:

$$v_i = v(a_i, w_i, P_i),$$

where P_i denotes the regional price index. This depends on the consumption aggregator $g(\cdot)$.

Workers location choice. Each worker draws an idiosyncratic preference shock ε_i for each region, distributed Fréchet with shape parameter ν.[9] Workers choose locations to maximize utility including preference shocks,

$$\max_i\ v_i \varepsilon_i.$$

The resulting population distribution then satisfies,

$$L_i = \frac{v_i^\nu}{\sum_j v_j^\nu} \bar{L}. \tag{1.7}$$

In the quantitative model, I assume no migration costs between regions. Section 1.6 introduces migration costs to assess robustness to this assumption.

Aggregate consumption and trade balance. Each region also contains immobile landowners who rent land to firms and consume goods locally using the same preferences as

[9] I allow for preference shocks since this is general enough to subsume the case with free mobility. If we assume $\nu \to 0$, the model collapses into one with free mobility where the migration condition would require $v_i = vj\ \forall i, j \in N$. Further, I consider multiplicative shocks here. An alternative formulation would be to have additive shocks such that workers solve:

$$\max_i\ v_i + \varepsilon_i.$$

This also impacts purely how cross regional transfers work, but not the results on optimal industrial policy. See Donald et al. (2025) for more details.

workers. I denote landlord consumption in region i from region-sector (j,k) as $c^l_{i,jk}$.

Let $C_{i,jk} = L_i c_{i,jk} + c^l_{i,jk}$ denote total consumption of good (j,k) in region i across both workers and landowners. I impose that trade is balanced within each region, so total income across workers and landowners equals total expenditure:

$$w_i L_i + r_i H_i = \sum_{j=1}^{N} \sum_{k=1}^{K} (\tau_{ji} p_{jk}) C_{i,jk}$$

This balanced trade condition reflects that all income earned in region i, from both labor and land, is spent on consumption within that region. This equation is implied by the budget constraints on workers and local landowners.

1.2.3 Market clearing

In equilibrium, the output, land, and labor markets clear. For any sector-region pair, goods market clearing requires,

$$q_{ik} = \sum_{j=1}^{N} \tau_{ij} C_{j,ik} \quad \forall\ k, i. \tag{1.8}$$

Labor market clearing requires,

$$\sum_{k=1}^{K} L_{ik} = L_i \quad \forall\ i. \tag{1.9}$$

We also require the aggregate labor market to clear such that $\sum_i L_i = \bar{L}$ which is implied by the migration equation (1.7). Land market clearing requires,

$$\sum_{k=1}^{K} H_{ik} = \bar{H}_i \quad \forall\ i. \tag{1.10}$$

1.2.4 Equilibrium

We are now ready to define an equilibrium.

Definition 1.2.1. Given consumption parameters, production parameters, congestion and spillover elasticities $\{\theta, \phi_k\}$, productivity structure parameter $\{\iota\}$, location fundamentals $\{\bar{a}_i, \bar{z}_{ik}\}$, trade costs $\{\tau_{ij}\}$, initial population $\{\bar{L}\}$, and land supply $\{\bar{H}_i\}$, the equilibrium is a population distribution across regions $\{L_i\}$, across sectors within a region $\{L_{ik}\}$, land allocation across sectors within a region $\{H_{ik}\}$, quantities $\{q_{ik}, C_{i,jk}\}$, prices $\{p_{ik}, w_i, r_i\}$, and location technologies $\{a_i, z_{ik}\}$ such that:

1. Region-sector productivities are given by equation (1.1).
2. Labor allocation across sectors in each region is given by equation (1.2).
3. Land allocation across sectors in each region is given by equation (1.3).
4. Prices are given by (1.4).
5. Amenities are given by equation (1.5).
6. Consumption is chosen in accordance with equation (1.6).
7. Workers make migration decisions captured by equation (1.7).
8. All markets clear as given in equations (1.8, 1.9, 1.10).

1.2.5 Model discussion

The model embeds standard spatial trade and labor market forces that jointly determine the distribution of workers across regions and sectors. Two opposing mechanisms shape equilibrium outcomes. Agglomeration forces concentrate workers in space, and congestion forces spread workers across space.

Agglomeration arises through two channels. First, sector specific externalities, captured by the elasticity parameter ϕ_k, make region-sector productivity increase with local sectoral employment. Second, standard home market effects imply that, in the presence of trade costs, workers benefit from locating in regions with large local demand and low price indices. The latter is a pecuniary force rather than an externality but nonetheless reinforces spatial concentration.

Congestion/dispersion forces operate through several mechanisms. The congestion elasticity θ reduces local amenities as regional population rises, representing a true externality. Additional non external congestion arises from the fixed supply of land, which raises rents in dense regions, and from heterogeneity in workers' idiosyncratic location preferences. The Fréchet shape parameter ν governs this heterogeneity. A higher ν implies more dispersed preferences and thus a more even spatial distribution of population.

Finally, equilibrium differences across regions arise endogenously from four types of heterogeneity:

1. **Market access:** Trade costs generate unequal access to other regions' markets.
2. **Fundamental productivity:** Each region-sector has a distinct baseline productivity $\bar{z}_{ik}$.
3. **Amenities:** Each region possesses a base amenity level $\bar{a}_i$, shaping its attractiveness to workers.
4. **Land supply:** Total land in each region is fixed, influencing both factor prices and spatial allocation.

Together, these elements interact with agglomeration and congestion forces to determine the spatial organization of production and employment across sectors.

1.3 Optimal allocations

This section characterizes the optimal allocation of resources and the policy instruments that can implement it in equilibrium. I proceed in four steps. First, I formulate the social planner's problem which provides a benchmark for efficient allocations when all externalities are internalized. Second, I identify the underlying sources of inefficiency in the decentralized equilibrium by examining the necessary conditions for the social planner. Third, I derive the policy instruments that decentralize the planner's allocation, showing how targeted subsidies and taxes can restore efficiency. I discuss the intuition behind these instruments and examine limiting cases of the productivity structure parameter ι to clarify when and why place-based industrial policy is warranted. Finally, I present the welfare implications of the derived policy instruments when there is parameter uncertainty.

1.3.1 The Social Planner's Problem

I begin by characterizing the allocation that maximizes aggregate welfare in this economy. The planner chooses the distribution of workers across regions $\{L_i\}$ and across sectors within regions $\{L_{ik}\}$, land allocation across sectors within regions $\{H_{ik}\}$, workers' consumption for each region-sector's output $\{c_{i,jk}\}$, aggregate worker consumption $\{c_i\}$, and landlord consumption for each region-sector's output $\{c^l_{i,jk}\}$.

Workers receive idiosyncratic preference shocks over regions, drawn from a Fréchet distribution with shape parameter ν, which governs the elasticity of migration responses. The planner maximizes the expected ex-ante utility of a representative worker. Namely, this is the welfare of an agent before the realization of the idiosyncratic preference shock

$$W = \Gamma\left(\frac{\nu-1}{\nu}\right)\left(\sum_i (a_i c_i)^\nu\right)^{1/\nu}, \tag{1.11}$$

where $\Gamma(\cdot)$ is the gamma function. This formulation implies that worker utility depends on

both real aggregate consumption and the attractiveness of each location.

A key restriction of the planner's problem is that workers are freely mobile. The planner cannot directly assign workers to regions but must respect the spatial mobility constraint, which ensures that regional populations are consistent with individual location choices such that

$$L_i = \frac{(a_i c_i)^\nu}{\sum_j (a_j c_j)^\nu} \bar{L}, \tag{1.12}$$

where $\bar{L}$ is the total labor force. This constraint distinguishes the planner's problem from a purely command allocation, i.e, the planner must operate accounting for the equilibrium location choice of workers. The planner then maximizes (1.11) subject to the migration decision by workers given by equation (1.12) which is the spatial mobility constraint, the output market clearing for each region-sector subject to trade costs (1.8), labor allocation across sectors for each region (1.9), land allocation across sectors for each region (1.10), and the consumption aggregator which I parameterize to be nested CES. The planner's optimization problem can then be written as

$$\begin{aligned}
\mathcal{L} = \max_{\{L_i, L_{ik}, H_{ik}, c_i, c_{i,jk}, c^l_{i,jk}\}} & \Gamma\left(\frac{\nu-1}{\nu}\right)\left(\sum_{i=1}^{N}(a_i c_i)^\nu\right)^{1/\nu} \\
& + \sum_i \eta_i \left[c_i - \left(\sum_k \kappa_k^{1/\sigma} \left(\sum_j c_{j,ik}^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi(\sigma-1)}{\sigma(\psi-1)}} \right)^{\frac{\sigma}{\sigma-1}} \right] \\
& + \sum_i \mu_i \left[L_i - \frac{(a_i c_i)^\nu}{\sum_j (a_j c_j)^\nu} \bar{L} \right] + \sum_i \tilde{w}_i \left[L_i - \sum_k L_{ik} \right] \\
& + \sum_i \tilde{r}_i \left[\bar{H}_i - \sum_k H_{ik} \right] \\
& + \sum_i \sum_k \tilde{p}_{ik} \left[z_{ik}^\iota f_k(z_{ik}^{1-\iota} L_{ik}, H_{ik}) - \sum_j \tau_{ij} C_{j,ik} \right],
\end{aligned}$$

This optimization problem embeds two potential sources of inefficiency in the spatial allocation of workers. There is misallocation across regions (for given total population $\bar{L}$) and

misallocation within regions across sectors (for given regional population L_i). Both distortions motivate policy intervention in subsequent sections. The planner's solution provides a benchmark for identifying the wedges that make the competitive equilibrium inefficient and the policy instruments required to eliminate them.

1.3.2 Misallocation across regions

Before analyzing the role for industrial policy, I first characterize optimal consumption per worker in each region. Since workers make their optimal location decisions accounting for their consumption in those regions, a difference in optimal consumption per worker relative to the competitive equilibrium induces a reallocation of workers. This is the same result as Fajgelbaum and Gaubert (2020) and Rossi-Hansberg et al. (2025), modified for the setting in this paper. In the optimal allocation, consumption per worker is given by

$$\tilde{P}_i c_i = \frac{\nu}{1+\nu}\tilde{w}_i + \Lambda, \tag{1.13}$$

where Λ is a constant determined such that $\Gamma(\frac{\nu-1}{\nu})W = \sum_i L_i \tilde{P}_i c_i$ holds and $\tilde{P}_i$ is an index of the lagrange multipliers on the output for each region-sector accounting for trade costs such that

$$\tilde{P}_i := \frac{-\eta_i}{L_i} = \left(\sum_k \left(\sum_j (\tilde{p}_{jk}\tau_{ji})^{1-\psi}\right)^{\frac{1-\sigma}{1-\psi}}\right)^{\frac{1}{1-\sigma}}.$$

I derive this in the Appendix A4.1. Here $\tilde{w}_i$ represents the social marginal product of a worker in region i which deviates from the private marginal product of a worker in region i because of region-sector agglomeration externalities ϕ_k. The value of private marginal product represents the wage in the competitive equilibrium which needs to be adjusted. Adjustment in this wage consequently impacts the distribution of workers in space by affecting the consumption per worker.

Further, note that consumption increases less than one for one with marginal productivity, reflecting the fact that workers have heterogeneous idiosyncratic preferences between regions. The marginal worker in high wage cities must have lower average preference draws (otherwise more would migrate there), so the planner optimally transfers resources from high to low wage locations. This transfer is not region specific but reflects the overall Fréchet distribution of preferences, resulting in a uniform dampening factor $\frac{\nu}{1+\nu} < 1$ everywhere. As $\nu \to \infty$, this factor approaches unity and consumption moves one to one with the marginal product.[10]

1.3.3 Misallocation across sectors within regions

I now highlight the role for place-based industrial policy by characterizing the misallocation that arises within each region in the competitive equilibrium.

Proposition 1.3.1. *In the planner's allocation, the marginal social value of labor is equalized across all sectors $k, k' \in \{1, \ldots, K\}$ within each region i. This implies that*

$$\tilde{p}_{ik} z_{ik} f'_{k,1}(1 + (1-\iota)\phi_k) + \iota \phi_k y_{ik} = \tilde{p}_{ik'} z_{ik'} f'_{k',1}(1 + (1-\iota)\phi_{k'}) + \iota \phi_{k'} y_{ik'}, \tag{1.14}$$

where $y_{ik} = \frac{\tilde{p}_{ik} q_{ik}}{L_{ik}}$ is the value of output per worker and $f'_{k,1} = \frac{\partial f_k}{\partial (z_{ik}^{1-\iota} L_{ik})}$ is the marginal product of effective labor.

Proof. See Appendix A4.2.

This condition implies that the planner equates the social marginal value of an additional worker across all sectors within each region. By contrast, the competitive equilibrium equalizes only the private marginal product of labor. As a result, the competitive equilibrium fails to achieve this social optimum when agglomeration spillovers are present. This serves as the rationale for sectorally targeted industrial policy.

[10] Note that this source of inefficiency exists even in the absence of congestion and agglomeration externalities. As discussed in Mongey and Waugh (2024), this happens because of a lack of complete markets which implies workers cannot insure themselves against adverse preference shocks. Ex-ante, workers would like to equalise their marginal utilities of consumption across all states of the world which they cannot achieve in the competitive equilibrium.

The planner's first-order condition can be decomposed into three distinct components that clarify how the structure of productivity externalities shapes optimal allocations.

(i) Private marginal product. The term $\tilde{p}_{ik} z_{ik} f'_{k,1}$ represents the private marginal product of labor. In the decentralized equilibrium, competitive wages equate this term across sectors in each region ensuring that a worker's private contribution to output is identical across sectors. This reflects the direct productivity contribution of an additional worker, holding productivity fixed.

(ii) Harrod-neutral externality component. The term $(1 - \iota)\phi_k \tilde{p}_{ik} z_{ik} f'_{k,1}$ captures externalities that operate purely through labor productivity. When $\iota = 0$ (pure Harrod-neutrality), agglomeration effects raise the efficiency of workers but leave the productivity of other factors unchanged. Because this externality acts on the same margin as the private return to labor, it effectively scales up the private marginal product by the agglomeration elasticity ϕ_k. The planner internalizes this amplification, whereas individual workers and firms do not.

(iii) Hicks-neutral externality component. The term $\iota \phi_k y_{ik}$ captures externalities that raise the productivity of all factors proportionally. When $\iota = 1$ (pure Hicks-neutrality), agglomeration enhances the overall efficiency of production rather than labor productivity alone. In this case, the relevant margin is the value of output per worker, y_{ik}, since an additional worker increases the productivity of labor as well as all other factors of production. The externality scales up the value of output per worker in each region-sector by the agglomeration elasticity ϕ_k. This contrasts with the Harrod-neutral case, where the externality simply scales up the private marginal product of labor.

Intuitively, Harrod-neutral externalities operate through labor productivity, while Hicks-neutral externalities operate through the overall efficiency of production. The planner internalizes both channels, assigning labor across sectors to equalize the social rather than the private marginal product. This distinction highlights why estimating the underlying productivity structure is crucial. The nature of the externality determines the design and

magnitude of the policy intervention required to restore efficiency. The next subsection characterizes the policy instruments that decentralize the planner's allocation by aligning private incentives with these sector and region specific social returns.

1.3.4 Decentralizing optimal allocations

The planner's allocation can be implemented in a decentralized economy using a combination of taxes, transfers, and sectoral subsidies. Before introducing the relevant policy instruments, it is useful to note that not all externalities in the model generate inefficiencies. Because congestion is parameterized by a constant elasticity $\theta > 0$ that applies uniformly across regions, moving a worker to any location imposes the same marginal congestion cost. As a result, congestion effects are symmetric and cancel out in the planner's solution. The only distortions that require correction therefore arise from (i) idiosyncratic preference shocks that distort regional consumption, and (ii) agglomeration externalities, captured by ϕ_k, that generate wedges between private and social marginal products.

Proposition 1.3.2. *The optimal allocation can be decentralized through a combination of instruments, which can be written as*

1. *Industrial subsidies composed of a constant ad-valorem wage subsidy s_k and a region specific per-worker subsidy s_{ik}:*

$$s_k = \frac{(1-\iota)\phi_k}{1+(1-\iota)\phi_k},$$
$$s_{ik} = \frac{\iota\phi_k}{1+(1-\iota)\phi_k}\frac{p^*_{ik}z^*_{ik}f_k(L^*_{ik},H^*_{ik})}{L^*_{ik}},$$

   where starred variables denote values at the planner's allocation.

2. *A constant income tax and transfer such that consumption per worker in each region*

satisfies

$$P_i c_i = (1 - t_L) w_i + \Lambda,$$

where $t_L = \frac{1}{1+\nu}$ *and* Λ *is chosen such that* $\Gamma\left(\frac{\nu-1}{\nu}\right) W = \sum_i L_i P_i c_i$. *Industrial subsidies are financed by regional land rents, with residual rents rebated lump sum to workers.*

Proof. See Appendix A5.1.

This proposition shows that optimal policy requires instruments that align private incentives with the social marginal value of labor derived in the planner's problem. The income tax and transfer correct for consumption in each region, while the industrial subsidies target agglomeration spillovers. The relative importance of the two industrial subsidy components depends on the structure of productivity externalities.

Harrod-neutral case ($\iota = 0$). When agglomeration externalities affect production purely through Harrod-neutral productivity, optimal industrial policy simplifies to a constant ad-valorem wage subsidy given by

$$s_k = \frac{\phi_k}{1 + \phi_k}.$$

There is no need for place-based industrial policies. Crucially, since wages capture the private marginal product of workers across regions in the competitive equilibrium, optimal industrial policy simply scales up wages proportionally by ϕ_k for any given sector k across all regions. This creates a natural case for uniform sectoral ad-valorem wage subsidies that do not require region specific information, but only information about the agglomeration elasticity ϕ_k. This result exploits the fact that competitive wages already reflect the private marginal valuation of a worker, and that firms use this price to make hiring decisions.

Hicks-neutral case ($\iota = 1$). When agglomeration externalities affect production purely through Hicks-neutral productivity, optimal industrial policy requires region and sector per

worker subsidies proportional to optimal revenue per worker given by

$$s_{ik} = \phi_k \frac{p^*_{ik} z^*_{ik} f_k(L^*_{ik}, H^*_{ik})}{L^*_{ik}}.$$

Because the externality now enhances the productivity of all factors of production, policy can no longer target only the private marginal product of labor captured by competitive wages. Instead, the planner must target the optimal revenue per worker, which varies systematically across space. Its variation across regions arises from differences in regional fundamentals such as productivity, market access, land endowments, and amenities. These are the sources for variation in industrial composition across regions present in the model in this paper. In richer settings, additional forces such as migration costs, commuting frictions, land supply constraints, or housing market heterogeneity could further shape this pattern. The largest subsidies therefore accrue to regions with the highest optimal revenue per worker in the targeted sector k. The case for place-based industrial policy thus arises not from differences in agglomeration elasticities across space, but from the heterogeneity in the economic geography that determines where production is most socially valuable.

For intermediate values of $\iota \in (0, 1)$, both externality channels are operative, and the planner requires a combination of the two instruments, i.e, a uniform ad-valorem wage subsidy and a spatially differentiated per-worker subsidy. While both instruments technically vary across space through wages and revenues, the critical distinction lies in policy design and informational requirements. The Harrod-neutral component can be targeted using sector level estimates of ϕ_k, whereas the Hicks-neutral component requires knowledge of optimal regional revenue per worker, which depends on underlying economic fundamentals of each region.

The analysis reveals an information problem for policy design under Hicks-neutral productivity. Since the subsidy depends on revenue per worker at the optimal allocation, and not the observed equilibrium values, policymakers are required to have detailed knowledge of

regional fundamentals and their general equilibrium interactions which is information that may be difficult to obtain in practice. Like we just discussed, there are a large number of factors that could impact the optimal sector size across regions which makes targeting this externality challenging.

The set of policy instruments used to decentralize the planner solution highlights why estimating the productivity structure parameter ι is crucial for industrial policy design. The optimal policy framework depends on whether spillovers operate primarily through labor-augmenting (Harrod-neutral) or factor-neutral (Hicks-neutral) channels, with vastly different implementation requirements and welfare consequences.

To build further intuition on how optimal industrial policy depends on the productivity structure and the nature of agglomeration externalities, I analyze four extreme cases. These examples clarify how the required policy instruments evolve as the source and scope of externalities change.

Case 1: Uniform spillovers, Harrod-neutral productivity Consider a case where $\iota = 0$ and we have $\phi_k = \phi > 0 \ \forall k$. When all sectors feature identical agglomeration spillovers and productivity is Harrod-neutral, the social planner condition simplifies to

$$\tilde{p}_{ik} z_{ik} f'_{k,1}(1+\phi) = \tilde{p}_{ik'} z_{ik'} f'_{k',1}(1+\phi),$$
$$\tilde{p}_{ik} z_{ik} f'_{k,1} = \tilde{p}_{ik'} z_{ik'} f'_{k',1}, \quad \forall k, k'.$$

This exactly recovers the competitive equilibrium condition. Since the externality only scales up labor productivity uniformly across sectors, equalizing private marginal products also equalizes social marginal products. There is therefore no role for industrial policy. The competitive allocation of labor across sectors within each region is already efficient.

Case 2: Targeted spillovers, Harrod-neutral productivity Consider a case where $\iota = 0$, and we have $\phi_{k'} = \phi > 0$ and $\phi_k = 0 \ \forall k \neq k'$. This describes a world where

agglomeration spillovers exist in only one sector (the target of industrial policy). The social planner condition becomes

$$\tilde{p}_{ik} z_{ik} f'_{k,1}(1+\phi) = \tilde{p}_{ik'} z_{ik'} f'_{k',1}, \quad \forall k, k'.$$

The planner scales up the private marginal product in the targeted sector by the agglomeration elasticity ϕ in each region. Since this scaling factor is identical across locations, optimal policy requires only one instrument which is a constant ad-valorem wage subsidy to the targeted sector across all regions. This setting provides the simplest rationale for sectoral, but not spatially differentiated, industrial policy.

Case 3: Targeted spillovers, Hicks-neutral productivity Consider a case where $\iota = 1$, and we have $\phi_{k'} = \phi > 0$ and $\phi_k = 0 \ \forall k \neq k'$. This is the same sectoral targeting as the previous case, but now with Hicks-neutral productivity. The social planner condition becomes

$$\tilde{p}_{ik} z_{ik} f'_{k,1} + \phi y_{ik} = \tilde{p}_{ik'} z_{ik'} f'_{k',1}, \quad \forall k, k'.$$

Here the externality scales with the total value of output per worker, y_{ik}. As a result, optimal industrial policy requires N instruments. These are place-based subsidies per-worker to the targeted sector that vary with each region's optimal revenue per worker. In this environment, place-based industrial policy arises not because regions differ in ϕ_k, but because of the variation across the regions' economic fundamentals.

Case 4: Uniform spillovers, Hicks-neutral productivity Finally, consider a case where $\iota = 1$ and we have $\phi_k = \phi > 0 \ \forall k$. The social planner condition becomes

$$\tilde{p}_{ik} z_{ik} f'_{k,1} + \phi y_{ik} = \tilde{p}_{ik'} z_{ik'} f'_{k',1} + \phi y_{ik'} \quad \forall k, k'.$$

Despite identical agglomeration elasticities, sectoral misallocation persists because revenue per worker can differ across sectors within each region. The competitive equilibrium only equalizes the marginal product of workers, which does not need to imply that the average product per worker is equalized when sectors have different production functions. This contrasts sharply with Case 1, where identical spillovers eliminated any need for intervention. Optimal industrial policy now requires $N \times K$ instruments to address all sectoral misallocations within each region.

Table 1.1 summarizes the four cases analyzed above, showing how the combination of productivity structure (ι) and spillover patterns determines both the need for industrial policy and its optimal design.

Table 1.1: Optimal industrial policy design across productivity structures

Productivity structure	**Spillover Pattern**	**Policy Instruments**	**Industrial policy type**
Harrod-neutral	Uniform across sectors	0	No intervention needed
$\iota = 0$	$\phi_k = \phi > 0 \ \forall k$		
Harrod-neutral	Targeted sector only	1	Uniform ad-valorem
$\iota = 0$	$\phi_{k'} = \phi, \phi_k = 0 \ \forall k \neq k'$		wage subsidy
Hicks-neutral	Targeted sector only	N	Place-based subsidy
$\iota = 1$	$\phi_{k'} = \phi, \phi_k = 0 \ \forall k \neq k'$		per worker
Hicks-neutral	Uniform across sectors	N×K	Place-based subsidy
$\iota = 1$	$\phi_k = \phi > 0 \ \forall k$		per worker-sector

1.3.5 Welfare implications of policies across productivity structures

The decentralization results characterize what optimal industrial policy looks like conditional on a known productivity structure. In practice, however, policymakers may not be able to estimate ι precisely. Misidentifying whether spillovers are primarily labor-augmenting or factor-neutral could therefore lead to policy mistakes. It is thus informative to examine how different policy designs perform across the full range of $\iota \in [0, 1]$.

Proposition 1.3.3. *In an economy with agglomeration spillovers in a single targeted sector, such that $\phi_{k'} = \phi > 0$ and $\phi_k = 0$ for all $k \neq k'$, a uniform ad-valorem wage subsidy*

$$s_{ik'} = \frac{\phi}{1+\phi}$$

yields positive welfare gains for all $\iota \in [0, 1]$.

Proof. See Appendix A5.2.

This proposition establishes a key robustness property of uniform sectoral industrial policy. Even when the exact productivity structure is unknown, a uniform wage subsidy to the targeted sector improves welfare relative to laissez-faire. The economic mechanism operates through the relationship between marginal and average products of labor.

Uniform wage subsidies raise the private marginal product of labor which is sufficient to internalize the full externality under Harrod-neutral production ($\iota = 0$). When production is instead Hicks-neutral ($\iota = 1$), the total externality depends on average revenue per worker, which always exceeds the marginal product. As a result, uniform subsidies under correct the externality when $\iota > 0$. They generate positive but suboptimal welfare gains.

By contrast, place-based subsidies of the form

$$s_{ik'} = \phi_{k'} \frac{p^*_{ik'} z^*_{ik'} f_{k'}(L^*_{ik'}, H^*_{ik'})}{L^*_{ik'}},$$

which target optimal revenue per worker, achieve the first best only under Hicks-neutral production. When $\iota < 1$, these policies over correct the externality because the average product exceeds the true externality magnitude. Excessive targeting of the high productivity sector can then draw too many resources into it, potentially reducing welfare below the no-policy baseline.

These asymmetric welfare effects have important implications for policy design under uncertainty about the productivity structure. Uniform sectoral policies act as a welfare floor. They guarantee an improvement over laissez-faire regardless of ι. Place-based policies, in contrast, offer greater potential welfare gains when correctly specified but entail downside risk if the structure of spillovers is misidentified. This tradeoff highlights the informational challenge facing policymakers and underscores the importance of empirically estimating the productivity structure parameter ι, which governs not only the direction of optimal intervention but also the welfare consequences of getting it wrong.

1.4 Quantification: An application to industrial policy in England

This section presents the quantitative application of the theoretical framework to the UK's contemporary industrial strategy. I first describe why the UK's recent policy initiative provides an ideal setting for testing the model's predictions about optimal place-based industrial policy. I then detail the data sources, empirical methodology, and key estimation exercise that allow me to estimate the critical parameters identified in the theory.

1.4.1 Invest 2035: The UK's modern industrial strategy

In October 2024, the UK government launched "Invest 2035: The UK's Modern Industrial Strategy," a comprehensive 10-year plan designed to drive economic growth through targeted

sectoral interventions. This represents a significant shift in UK economic policy, explicitly acknowledging that "the case for governments to roll up their sleeves and shape markets rather than step back in the face of these challenges is stronger than ever." (UK Department for Business and Trade, 2025)

The strategy identifies eight "growth-driving sectors" for targeted support: advanced manufacturing, clean energy industries, creative industries, defence, digital and technologies, financial services, life sciences, and professional and business services. These sectors were selected based on their high productivity, international competitiveness, and potential for future growth. Importantly, sectoral targeting under Invest 2035 is motivated by efficiency considerations, prioritizing productivity and growth rather than national security or redistributive objectives. This alignment allows the welfare maximizing logic in the theoretical framework to map directly onto the government's stated policy goals.

What makes Invest 2035 particularly relevant for this study is its explicit emphasis on spatial targeting. The strategy aims to "concentrate government's efforts in places with the greatest potential for national prosperity and the growth driving sectors: in our city regions and high-potential clusters." By selecting regions based on their potential comparative advantage in each targeted sector, the policy embodies the same efficiency-based logic emphasized in the model.

While Invest 2035 highlights advanced manufacturing as a priority sector, the empirical analysis in this paper focuses on manufacturing as a whole. This broader definition is driven by data availability: regional land allocation data are only observable at the aggregate manufacturing level. Nonetheless, advanced manufacturing represents a substantial share of UK manufacturing activity. It accounts for nearly 40 percent of total manufacturing gross value added in 2022. As a result, the analysis captures a large portion of the sector directly targeted by policy.

1.4.2 Data

I quantify the model using data for 2021, the most recent UK census year. The analysis focuses on 153 regions across England, organized into two broad sectors: manufacturing and all other sectors such that $k \in \{m, o\}$.

The spatial unit of analysis consists of unitary authorities, counties, and metropolitan districts. These represent three distinct forms of local government:

Unitary Authorities are single tier local government areas that handle both county-level services (education, social services, highways) and district-level services (waste collection, housing, local planning). They were created to simplify administration by combining previously separate two-tier systems.

Counties represent the traditional county-level administrative areas within the two-tier system, handling county-level services while districts within them manage local services.

Metropolitan Districts operate in major urban areas such as Greater Manchester, West Midlands, and West Yorkshire. These function effectively as unitary authorities within metropolitan county areas, handling most local government functions.

The analysis covers 153 such administrative units across England.

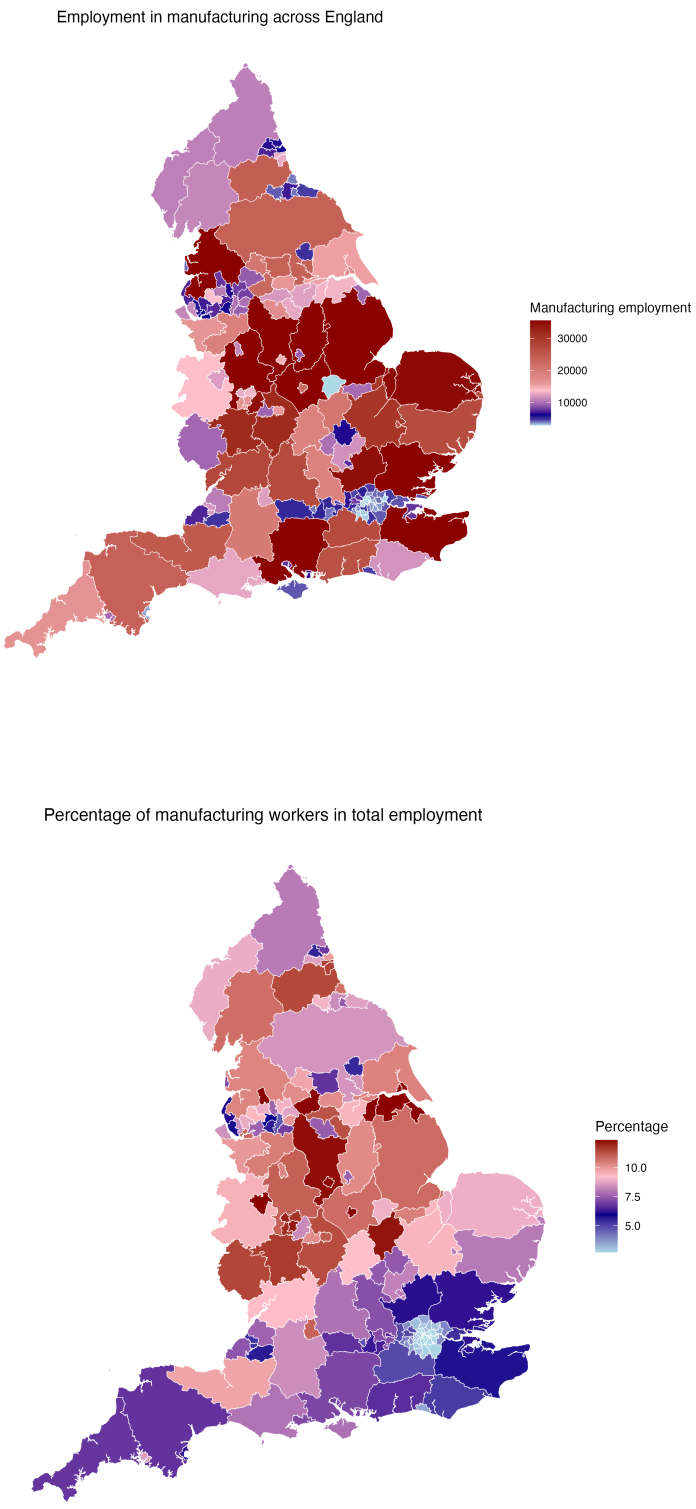


Figure 1.1: Distribution of manufacturing employment in England. Top: Total manufacturing employment across regions. Bottom: The percentage of employment accounted for by manufacturing across regions.

Manufacturing activity represents a substantial source of employment in the Midlands and Northern England, with several local economies in these regions reporting over 10 percent of their workforce in manufacturing. In contrast, London, the South East, and parts of the South West exhibit much lower manufacturing intensity, reflecting their greater specialization in services. This spatial heterogeneity underpins the regional variation in industrial policy effectiveness examined in later sections, as regions with stronger manufacturing bases are more directly affected by sector specific subsidies.

I obtain data on wages and the industrial composition of employment within each region from NOMIS, which is a labor market survey in the UK. I obtain data on rents within each region from the Price Index of Private Rents (PIPR) from the Office for National Statistics (ONS).

Data on land allocated to different uses comes from the UK government's official land use statistics for England. These statistics categorize land use into several broad categories including residential, transport and utilities, agriculture, forests, water, community services, minerals and landfills, and industrial uses.

For manufacturing land, I use the "industrial" category, which includes "works, refineries, shipbuilding yards, mills and other industrial sites" but explicitly excludes office and retail space. This provides a clean measure of land devoted to manufacturing production activities.

I further obtain data on the share of high-skilled workers (defined as those with university level qualifications), gender composition (share of male workers), and nativity composition (share of English born workers) in each region using NOMIS. I obtain climate data from the Met Office Climate Data Portal, including average annual precipitation, mean temperature, and the number of summer days (defined as days with maximum temperature above 25°C).

1.4.3 Calibrated parameters and functional forms

In this section, I describe the functional forms used for household preferences as well as firm production across all regions and sectors. I then explain the calibration strategy for various

model parameters.

I take the consumption aggregator function $g(\cdot)$ to be nested CES as defined below.

$$c_i = \left(\sum_k \kappa_k^{1/\sigma} c_{ik}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$
$$c_{ik} = \left(\sum_j c_{j,ik}^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}},$$

where σ is the elasticity of substitution across sectors, and ψ is the elasticity of substitution across regions within sector. κ_k represents the consumption share of sector k.

I calibrate $\kappa_m = 0.09$ to match the manufacturing share of GDP in 2021. I set the elasticity of substitution across regions $\psi = 3.8$ in line with the estimates from Bajzik et al. (2020). I calibrate the elasticity of substitution across different types of goods $\sigma = 2.8$, which is on the lower end of the estimates in Head and Mayer (2014) to account for the fact that substitutability across sectors would be lower than across regions for the same sector. The lower values for the elasticities of substitution make sense since I consider a coarser definition of sectors than the other papers.

In order to parameterize trade costs, I use the strategy from Redding (2016) where trade costs are a constant elasticity function of distance between the centroids of any two regions:

$$\tau_{ij} = \underbrace{d_{ij}^{\zeta}}_{\text{distance}},$$

where $\zeta = 0.33$.

I calibrate the Fréchet shape parameter $\nu = 3.0$, which corresponds to the elasticity of a location's labor supply with respect to its real income, to be consistent with the estimates in Bryan and Morten (2019) who estimate this parameter using Indonesian and US data.

Amenities in a given region are endogeneous in the number of people that live there, and face congestion parameterized by θ. There are various sources through how this channel operates including impact on traffic (Akbar et al., 2023), or public good provision (Craig,

1987), or through the housing market (Combes et al., 2019). Further, the literature has explored how preferences for a region's amenities respond to the composition of the local population (Handbury, 2021, Guerrieri et al., 2013, Bayer et al., 2007, Diamond, 2016). Duranton and Puga (2020) summarise these various sources and estimates. I calibrate the congestion parameter to $\theta = 0.6$, implying that a 1% increase in a region's population is associated with a 0.6% decrease in its amenities.

Lastly, I assume the production function for firms across all regions and sectors is CES such that:

$$q_{ik} = z_{ik}^{\iota}\left(\alpha_k^{1/\gamma}(z_{ik}^{1-\iota}L_{ik})^{\frac{\gamma-1}{\gamma}} + (1-\alpha_k)^{1/\gamma}H_{ik}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}},$$

where γ is the elasticity of substitution between land and labor, and α_k is the share parameter for workers in total production for manufacturing $k = m$ and other sectors $k = o$. I calibrate α_k to match the labor share in value added across manufacturing and other sectors such that $\alpha_m = 0.55$ and $\alpha_o = 0.62$.

Finally, I need to calibrate the elasticity of substitution between workers and land. Ciccone and Peri (2005) summarize estimates of the elasticity of substitution between skilled and unskilled labor in the literature to range from 1.36 and 2. Card (2001) estimate the elasticity of substitution across occupations to be 10. Chirinko and Mallick (2017) estimate the elasticity of substitution between workers and capital to be near 0.4. I calibrate the elasticity of substitution between workers and land to $\gamma = 2$ to lie roughly between the estimates across these literatures, and perform robustness checks for different values of γ.

1.4.4 Estimating productivity parameter and agglomeration externality

To determine optimal industrial policy design and quantify welfare gains, I need to estimate both ι and ϕ_m. I assume agglomeration externalities exist only in manufacturing ($\phi_m > 0$)

while setting $\phi_o = 0$ for other sectors.

I exploit the structure of the model to derive two regression equations that together identify the key parameters. The coefficients obtained from these regressions depend jointly on the values of both ι and ϕ_m. The first regression captures the elasticity of substitution between labor and land accounting for the productive agglomeration externalities accruing to workers. The second regression directly estimates the agglomeration externality of region–sector employment on region–sector productivity, where productivities are inferred from the model's equilibrium conditions.

This establishes two non-linear equations in $\{\iota, \phi_m\}$ which I can solve to obtain a unique estimate for both. The following subsections describe each estimation component before presenting results.

Elasticity of land with respect to labor

This equation follows the idea laid out in Doraszelski and Jaumandreu (2018) but isn't sufficient to estimate the productivity structure because of agglomeration externalities accruing in total workers.

The idea is that the elasticity of land with respect to labor depends on whether productivity is Hicks-neutral or Harrod-neutral, since agglomeration externalities affect land in only one of those specifications. For CES production, optimal factor choice for firms in region i and sector k implies

$$\frac{L_{ik}}{H_{ik}} = \frac{\alpha}{1-\alpha} z_{ik}^{(1-\iota)(\gamma-1)} \left(\frac{r_i}{w_i}\right)^{\gamma}.$$

Substituting the agglomeration specification $z_{ik} = \bar{z}_{ik} L_{ik}^{\phi_k}$ and rearranging yields the following regression equation,

$$\ln H_{ik} = \tilde{\alpha} + \gamma \ln \frac{w_i}{r_i} + \underbrace{\left(1 - (1-\iota)(\gamma-1)\phi_k\right)}_{=\beta} \ln L_{ik} + \tilde{z}_{ik}, \tag{1.15}$$

where $\tilde{\alpha} = \ln((1-\alpha)/\alpha)$ and $\tilde{z}_{ik} = (1-\iota)(1-\gamma)\ln \bar{z}_{ik}$ represents unobserved productivity fundamentals. This term is given by

$$\ln \bar{z}_{ik} = b_k Z_{ik} + \varepsilon_{ik},$$

where Z_{ik} are observable regional characteristics to control for underlying productivity, and ε_{ik} is unobserved city-region productivity which is the error in this regression.

The elasticity of land with respect to labor $\beta = 1 - (1-\iota)(\gamma-1)\phi_k$ is informative about the nature of productivity spillovers. Under pure Hicks-neutrality ($\iota = 1$), spillovers scale all factors proportionally, yielding $\beta = 1$ and recovering the standard CES relationship. As we move towards Harrod-neutrality ($\iota = 0$), spillovers augment only labor, creating $\beta < 1$. The deviation of β from unity thus measures how spillovers favor labor-augmenting versus factor-neutral productivity gains. Further, stronger agglomeration ϕ_m reduces the estimate for β since it makes land less substitutable with labor.

From the estimated β, I can recover the relationship between ι and ϕ_m conditional on the elasticity of substitution γ. Namely,

$$\iota = 1 - \frac{1-\beta}{\phi_m(\gamma-1)}.$$

A naive OLS estimation strategy is likely to yield biased estimates of β. The endogeneity issue is that regions with high unobserved productivity $\bar{z}_{ik}$ attract more employment, creating correlation between L_{ik} and the error term.[11] I address this through two complementary strategies.

Control variables. To address potential omitted variables bias, I include extensive controls into the regression: i) controls for the demographic characteristics of different regions such as the share of natives, gender split, and the share of high skilled workers, ii) climate

[11] Note that we also have this endogeneity concern for $\frac{w_i}{r_i}$ which makes estimating γ challenging. I calibrate this value from the literature since I lack an instrument for this variable

based determinants of regional productivity including variables that account for temperatures of the regions, the number of summer days, as well as rates of precipitation, and finally iii) fixed effects for different regions in England to absorb any historical or geographic determinants of local productivities in different places. For more details on the control variables, please refer to the Appendix (A6.2):

Instrumental variables. For remaining endogeneity, I exploit quasi-random historical variation in Polish immigrant populations. During WWII, there was a large influx of Polish migrants into Britain to aid with the war effort and these were concentrated in regions with military significance. Following the war, Britain established approximately 250 camps to house Polish military personnel and civilians, located based on military logistics rather than economic conditions. The Polish Resettlement Act of 1947, the first ever mass immigration legislation passed by the UK parliament, formalized settlement patterns with many Poles remaining near original camps due to social networks.

This historical placement creates contemporary spatial variation in Polish populations through network effects which reflects wartime military decisions rather than underlying economic fundamentals. The exclusion restriction then requires that the contemporary polish immigration density is uncorrelated with underlying fundamental regional manufacturing productivity, conditional on the controls in the regression, and as such affects manufacturing land purely through its effects on manufacturing employment which is likely given the military origins of camp placement which is uncorrelated with economic fundamentals of regions.

Table 1.2 presents results from estimating equation (1.15). The dependent variable is log manufacturing land use adjusted for the calibrated value of $\gamma = 2$. I present robustness checks with alternative values of γ in the Appendix (A6.3).

Table 1.2: Estimating land elasticity parameter β

	Adjusted Log Manufacturing Land	
	OLS	**IV**
Log Manufacturing Employment	1.087***	0.985***
	(0.100)	(0.125)
Controls	Yes	Yes
Observations	153	153
R^2	0.700	0.698
Weak instrument F-statistic	–	128.4

Notes: ***$p < 0.01$. Controls include skill composition, demographics, and climate variables. Weak instrument F-statistic tests relevance of Polish immigrant share.

The IV estimate of $\beta = 0.985$ suggests production in English manufacturing is close to Hicks-neutral, with minimal deviation from the standard CES case. However, we do not yet have a point estimate for ι since β also depends on ϕ_m. The point estimate for β establishes that

$$\iota = 1 - \frac{0.015}{\phi_m}. \tag{1.16}$$

Estimating agglomeration through inversion

In order to estimate the agglomeration elasticity for manufacturing ϕ_m, we need to first obtain a measure for regional manufacturing productivities.

Given parameters for the production function $\{\gamma, \iota, \alpha_k\}$, consumption aggregator $\{\sigma, \psi, \kappa_k\}$, fréchet shape parameter $\{\nu\}$, and data on wages and rents by region $\{w_i, r_i\}$, regional popula-

tions $\{L_i\}$, sectoral employment by region $\{L_{ik}\}$, trade costs $\{\tau_{ij}\}$, we can use the structural model to recover underlying region-sectoral productivities $\{z_{ik}\}$. The intuition for this lies in the fact that productivities affect sectoral labor demand in each region which I observe in the data. As such, productivities are the residuals which rationalize the observed distribution of workers across region and sectors in the data.

For example, if the Greater Manchester area has a high manufacturing workforce, paired with high local wages and rents, it must also have high productivity in manufacturing compared to other regions with low wages and rents but comparable workforce and market access. Given wages, rents, regional populations, consumption shares, and trade costs, we can obtain a measure of local demand for each region's output for each sector. Given production parameters, this allows us to determine the labor demand in each region sector. Further, given each region's wages and rents, we can infer the costs required to satisfy labor demand in equilibrium for each region-sector.

More specifically, we can write productivities in a region-sector as follows:

$$z_{ik} = \left(\alpha_k \kappa_k w_i^{-\gamma} L_{ik}^{-1} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma-\psi}{1-\gamma}} \sum_j \frac{\tau_{ij}^{-\psi} p_{jk}^{\psi-\sigma}}{p_j^{1-\sigma}} y_j \right)^{\frac{1}{\iota(1-\psi)+(1-\iota)(1-\gamma)}}. \tag{1.17}$$

The solution to this equation determines productivities. The derivation is provided in the Appendix A2.1.

In order to solve the model, we also need the distribution of amenities across regions $\{\bar{a}_i\}$. Given nested CES preferences for households and CES production for firms, I derive prices in equilibrium as a function of ι and productivities z_{ik} in the Appendix A1.2. These

prices can be written as,

$$p_{ik} = z_{ik}^{-\iota}\left(\alpha_k\left(\frac{w_i}{z_{ik}^{1-\iota}}\right)^{1-\gamma} + (1-\alpha_k)r_i^{1-\gamma}\right)^{\frac{1}{1-\gamma}}.$$

$$p_{i,jk} = \tau_{ji}p_{jk}$$

$$P_{ik} = \left(\sum_j p_{i,jk}^{1-\psi}\right)^{\frac{1}{1-\psi}}$$

$$P_i = \left(\sum_j \kappa_k P_{ik}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

As such, using the implied population share equation (1.7) and prices, we can obtain amenities up to scale using

$$\bar{a}_i \propto L_i^{\frac{1}{\nu}+\theta}\frac{P_i}{w_i}.$$

Once we have recovered manufacturing productivities $\{z_{im}\}$, we can use these to estimate the manufacturing agglomeration externality elasticity ϕ_m. Note that this measure of productivities is contingent on knowing ι, and as such, the estimated ϕ_m depends on the value of ι.

The model parameterizes productivities subject to spillovers in the sector size: $z_{im} = \bar{z}_{im}L_{im}^{\phi_m}$

$$\ln z_{im} = \phi_m \ln L_{im} + \ln \bar{z}_{im}, \tag{1.18}$$

where $\ln \bar{z}_{im}$ is underlying fundamental productivity level:

$$\ln \bar{z}_{im} = c_m Z_{im} + u_{im},$$

where Z_{im} are observable regional characteristics to control for underlying productivity, and u_{im} is unobserved city-region productivity which is the error in the regression.

Note that this regression equation suffers from the same endogeneity concerns as (1.15). We expect manufacturing employment in each region to be correlated with the underlying unobserved fundamental productivity.

I use the same set of controls and instrumental variable strategy to address these concerns in order to obtain an estimate of ϕ_m as a function of ι.

Iterative Estimation Procedure

The previous two subsections yielded two non-linear equations in $\{\iota, \phi_m\}$ which I can solve to obtain a unique estimate for each parameter. To recap, an estimate for β from regression equation (1.15) allows us to establish a closed-form relationship between both parameters. The inversion procedure and the corresponding estimate for the agglomeration elasticity from (1.18) establishes a numeric relationship between the two parameters. I use an iterative procedure to solve for each as described below:

1. I begin with an initial guess $\iota^0 \in [0, 1]$.
2. Use equation (1.17) to recover productivities z_{im}.
3. Estimate equation (1.18) to obtain ϕ_m.
4. Update ι using the constraint from β: $\iota^n = 0.1\iota^{n-1} + 0.9\left(1 - \frac{0.015}{\phi_k}\right)$.
5. Iterate until convergence $\iota^n \to \iota^{n-1}$.

Running this strategy yields an estimate $\iota^* = 0.906$, indicating that manufacturing productivity in England is predominantly Hicks-neutral with modest Harrod-neutral components. This would suggest that agglomeration externalities predominantly affect all factors of production, and are not purely labor augmenting. To show that there exists a unique estimate for ι, I plot both curves in the following figure

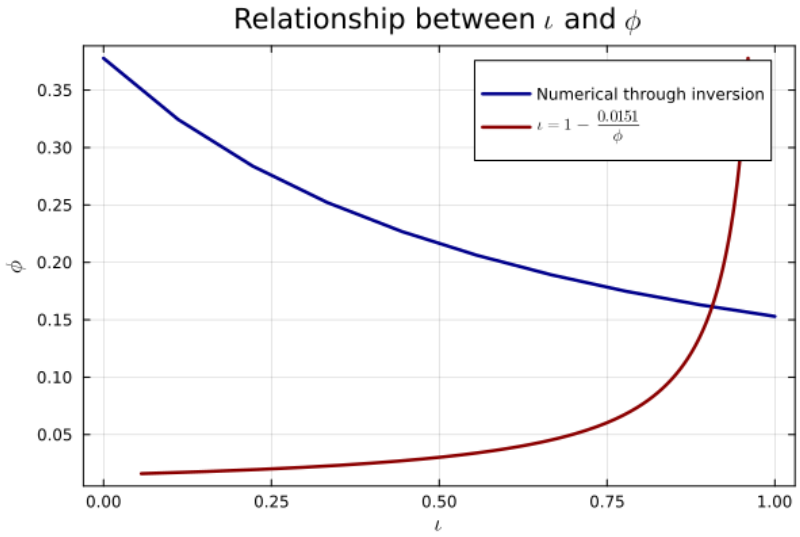


Figure 1.2: The blue line shows the relationship between ι and ϕ_m from the inversion procedure and the corresponding agglomeration estimation. The red line shows the closed-form relationship between ι and ϕ_m from estimating land elasticity. The curves intersect once at $\iota^* = 0.906$ which serves as our estimate.

This estimate provides a strong case to conduct place-based policies to support Manufacturing in England, which I quantify in section 1.5.

Agglomeration Results and Spatial Distribution of Fundamentals

Table 1.3 presents the final agglomeration estimates using the converged value of $\iota^* = 0.906$.

Table 1.3: Agglomeration Spillover Estimates

	Log Productivity	
	OLS	**IV**
Log Manufacturing Employment	0.186***	0.161***
	(0.019)	(0.024)
Controls	Yes	Yes
Observations	153	153
R^2	0.778	0.776
Weak instrument F-statistic	–	289.7

Notes: $^{***}p < 0.01$. Same controls and instrument as in Table 1.2.

The agglomeration elasticity estimate of $\phi_m = 0.161$ for manufacturing requires careful interpretation relative to the existing literature. Conventional city-level agglomeration studies typically find elasticities of 0.04-0.08 (Combes and Gobillon, 2015). For instance, Ciccone and Hall (1996) and Rosenthal and Strange (2008) estimate productivity elasticities with respect to regional density around 0.04-0.05 for the US, while Ciccone (2002) finds similar magnitudes ($\approx$0.05) for a host of European countries including the UK in 1992.

However, my estimate aligns closely with studies that, like this paper, examine sectoral agglomeration. Brülhart and Mathys (2008) estimate agglomeration externalities at the industry level using European regional data across 8 broad sectors including manufacturing, finding an agglomeration elasticity of 0.13. Their higher estimate is more in line with the agglomeration estimate in this paper.

This finding is also consistent with the results from Greenstone et al. (2010), who find

that manufacturing plant openings generate larger spillovers for incumbent firms in the same two-digit industry compared to different industries. They estimate an increase in TFP for plants in the same two-digit industry at a statistically significant 17% (compared to 4-5% at a regional level). Their framework suggests that agglomeration externalities strengthen as economic similarity increases.

My estimate also falls within the range of 0.11-0.31 reported by Bartelme et al. (2025) for sector-level scale elasticities for every two-digit manufacturing sector, though their estimates capture national-level returns to scale rather than local agglomeration effects.

Using the estimated parameters, I recover the spatial distribution of underlying amenities and manufacturing productivity fundamentals across English regions.

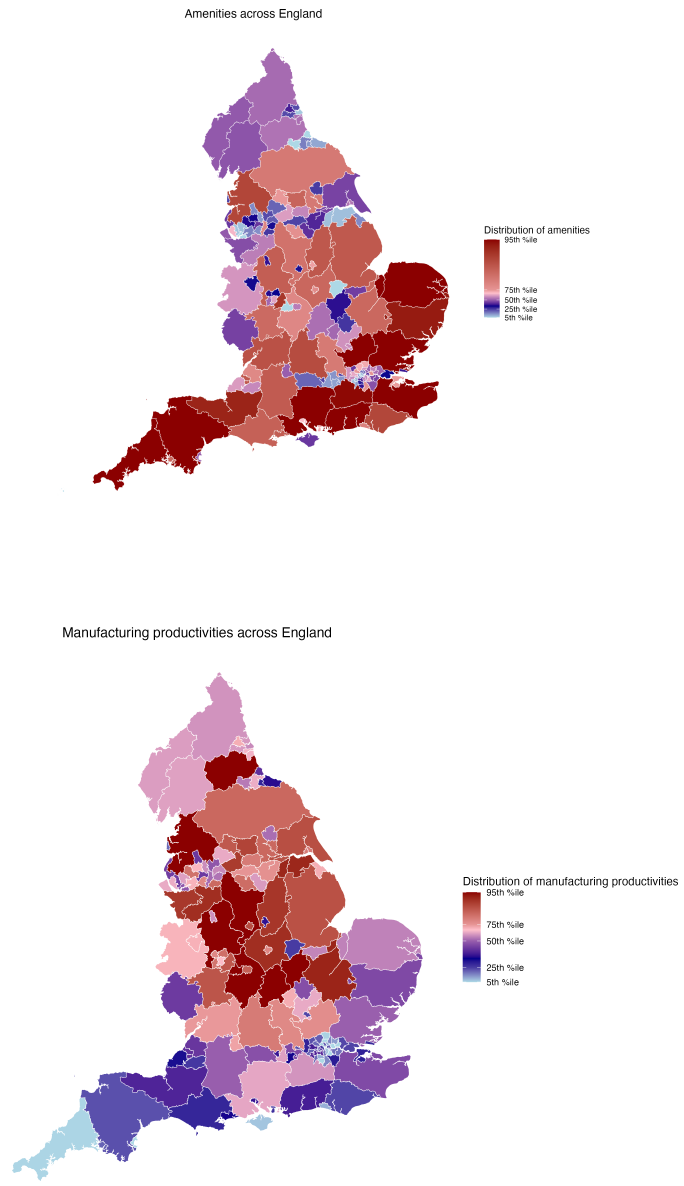


Figure 1.3: Top: Distribution of amenities $\bar{a}_i$ across England. Bottom: Distribution of manufacturing productivity $\bar{z}_{im}$ across England.

The model implied distribution of amenities shows that amenity levels are highest in regions with large populations and relatively lower wages, as high amenities are necessary to rationalize the observed population distribution given economic fundamentals. In practice, this pattern identifies regions in the East of England, the South-East, and South-West as

some of the highest amenity areas in England, consistent with their high populations and enduring attractiveness despite lower real wages relative to population. These include regions like Kent, Essex, Surrey, and Hertfordshire. Other notable high amenity regions include Lancashire, North Yorkshire, Nottinghamshire. These spatial patterns are consistent with the theoretical mechanism whereby high amenities sustain population concentration even when real wages are relatively low, thereby shaping the equilibrium population distribution.

Manufacturing productivities are highest in the North-East, the West Midlands, as well as some regions in the South-East. These include regions like Birmingham, West Northamptonshire, Lancashire, and Durham. In the South-East, regions like Surrey exhibit high manufacturing productivity.

1.5 The welfare gains from industrial policy

In this section, I use the estimated and calibrated parameters to quantify the welfare effects of implementing the industrial policies implied by the theoretical model. To begin, I evaluate the welfare consequences of implementing the optimal industrial policy mix under the estimated parameter values of $\iota^* = 0.906$ and $\phi_m = 0.161$.

I compute the optimal industrial policy mix as a combination of a constant ad-valorem wage subsidy (s_m^*) and a region specific per-worker subsidy to the manufacturing sector (s_{im}^*), which can be written as

$$s_m^* = \frac{(1-\iota^*)\phi_m}{1+(1-\iota^*)\phi_m} = 0.014$$
$$s_{im}^* = \frac{\iota^*}{1+(1-\iota^*)\phi_m}\phi_m \frac{p_{im}^* q_{im}^*}{L_{im}^*} = 0.144 * \frac{p_{im}^* q_{im}^*}{L_{im}^*}$$

where $\frac{p_{im}^* q_{im}^*}{L_{im}^*}$ is the optimal manufacturing revenue per worker in a given region i. The resulting policy mix relies primarily on place-based per-worker subsidies combined with a small uniform wage subsidy (1.4%). This reflects the predominantly Hicks-neutral productivity

structure for manufacturing in England.

To isolate the welfare effects arising solely from the industrial subsidy, I abstract from the consumption tax and lump sum transfer that accompany the full optimal policy package. Under this partial implementation, the subsidies yield an aggregate welfare gain of approximately 4.8 percent relative to the competitive equilibrium without policy intervention.

Figure 1.4 displays the optimal place-based subsidies per manufacturing worker across English regions under our estimated productivity structure. The spatial distribution reveals several noteworthy patterns that reflect the underlying economic geography of England.

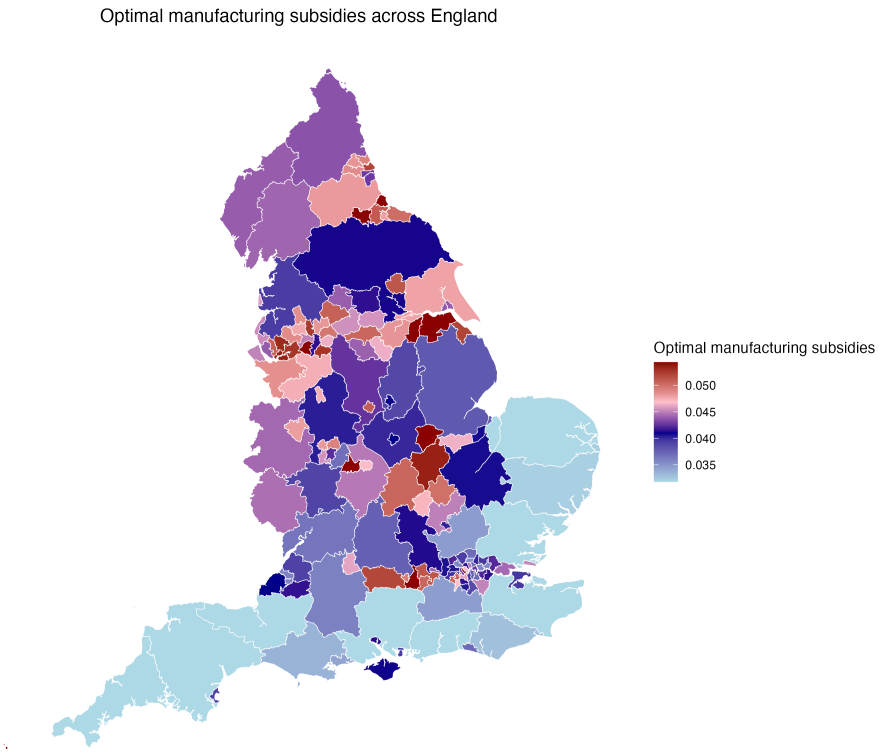


Figure 1.4: The distribution of manufacturing subsidies per worker

The distribution does not necessarily reflect the highest manufacturing revenue regions in England, but the highest *manufacturing revenue per worker* regions.

The North West receives some of the highest per-worker subsidies, particularly in Bury, Trafford, and St Helens. These are industrial districts situated near Manchester which is a center of textile production. This concentration of support reflects the region's role as one

of England's leading contributor to manufacturing value added.

Substantial allocations are also observed in the West Midlands, especially around Birmingham, where a strong automotive and metalworking base underpins the region's industrial ecosystem. Similarly, in the North East, several areas near Newcastle receive high subsidies, consistent with the presence of enduring steel and shipbuilding clusters. These allocations align closely with the argument that policy support is most efficient when directed toward regions with the largest revenues per worker.

The South East displays pronounced variation in subsidy intensity. While many areas receive limited support, regions such as Wokingham and West Berkshire stand out with relatively large subsidies per worker. These areas host a concentration of advanced and high value manufacturing, contrasting with nearby Surrey and West Sussex, where production is more service-oriented and receives little support. The uneven distribution within the South East illustrates how industrial policy selectively targets high productivity manufacturing enclaves, even within broadly prosperous regions. Regions in Yorkshire and the Humber also receive sizable subsidies, reflecting their continued strength in manufacturing and high sectoral productivity.

In contrast, areas in the South West and in London receive relatively little support, consistent with their weaker manufacturing presence and greater specialization in services. Overall, the spatial pattern of subsidies reflects a clear alignment with underlying industrial geography: support is concentrated in regions where manufacturing remains both economically significant and productivity enhancing, rather than allocated on redistributive grounds. This geographic selectivity underscores the central implication of the model—that optimal industrial policy should reinforce existing productive agglomerations where returns to intervention are highest.

1.5.1 Alternative policy designs

The first best industrial policy requires knowledge of the underlying productivity structure parameter ι and the optimal manufacturing revenue per worker in each location, which reflects both general equilibrium effects and optimal factor reallocation. In practice, policymakers observe only current equilibrium revenues, which may deviate from their optimal counterparts due to existing distortions. This section evaluates the welfare performance of implementable policy rules that rely on observable data to approximate the first best targeting scheme.

I compare four policy approaches:

1. **Optimal place-based industrial policy (Optimal PBIP).** The optimal policy under $\iota^* = 1$ (pure Hicks-neutral productivity) with no uniform component. Subsidies s^*_{im} target optimal manufacturing revenue per worker in each region such that

$$s^*_{im} = \phi_m \frac{p^*_{im} q^*_{im}}{L^*_{im}} = 0.161 \frac{p^*_{im} q^*_{im}}{L^*_{im}}$$

2. **Uniform wage subsidy.** The optimal policy under $\iota^* = 0$ (pure Harrod-neutral productivity) with no place-based component. This corresponds to a constant ad-valorem wage subsidy across all regions s^*_m such that

$$s^*_m = \frac{\phi_m}{1 + \phi_m} = 0.139.$$

3. **Constrained place-based industrial policy (Constrained PBIP).** A practical variant that uses *observed* rather than optimal manufacturing revenues to approximate the first best rule. These subsidies can then be expressed as

$$s_{im} = \phi_m \frac{p^{obs}_{im} q^{obs}_{im}}{L^{obs}_{im}}.$$

This design captures realistic policy settings where governments base support on current industrial activity without information on regional fundamentals and complex general equilibrium effects.

4. **Geographic targeting.** A further restriction that limits place-based subsidies to only regions with the highest observed manufacturing revenue per worker—mimicking policies that concentrate support in established industrial clusters. I evaluate scenarios with support restricted to the top 20 and top 10 manufacturing regions (in terms of manufacturing revenue per worker), respectively.

Figure 1.5 reports the welfare gains from each approach relative to the no-policy baseline.

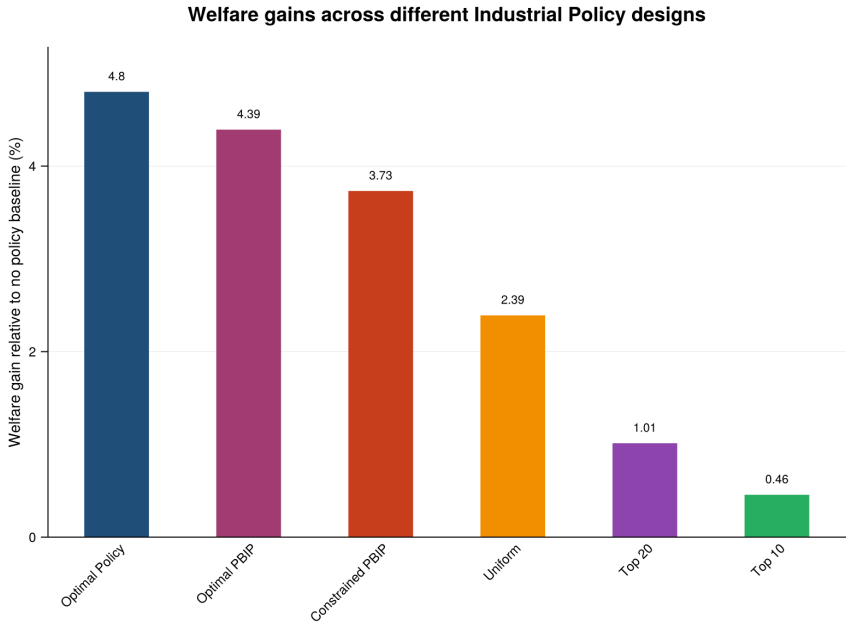


Figure 1.5: Welfare gains across alternative industrial policy designs. "Optimal Policy" corresponds to the estimated mixed case with both uniform and place-based components. "Optimal PBIP" and "Uniform" represent the pure Hicks- and Harrod-neutral cases. "Constrained PBIP" uses observed revenue per worker for all regions. "Top 20" and "Top 10" refer to geographic targeting based on the highest observed manufacturing revenues.

The welfare ranking of policies closely mirrors the underlying productivity structure estimated in the model. Because the estimated $\iota^* \approx 0.9$ implies a predominantly Hicks-neutral form of productivity, the purely place-based optimal policy captures nearly all of the

welfare gains from the combined optimal policy. This reflects that most of the externalities operate through factor neutral channels, which require region and sector specific subsidies that scale with local manufacturing activity.

By contrast, the uniform wage subsidy, which is optimal only under purely Harrod-neutral productivity, fails to exploit these spatial differences and therefore achieves substantially smaller gains. The welfare gap between the optimal place-based policy (4.4 percent) and the uniform subsidy (2.4 percent) quantifies the cost of ignoring geographic variation in the returns to industrial policy when the productivity structure is predominantly Hicks-neutral.

As such, it becomes important to be able to implement place-based industrial policies. The constrained place-based policy, which relies on observed rather than optimal manufacturing revenues, performs remarkably well—capturing about three quarters of the first best gains. This suggests that governments can approximate efficient spatial targeting even with limited information, provided policies respond to observed patterns of industrial concentration.

Finally, narrow geographic targeting exhibits sharply lower returns. Restricting subsidies to only the top 20 manufacturing regions yields welfare gains of 1%, while limiting support to the top 10 regions generates just 0.46%. This pattern indicates that the welfare gains from place-based policy arise from broad spatial differentiation rather than concentration in a few high performing areas. The underlying mechanism reflects that manufacturing agglomeration benefits are distributed across many regions in England, not confined to the most visible industrial centers. Narrowly targeted interventions thus fail to correct externalities in smaller, yet still productive, manufacturing locations across the broader economic landscape.

1.5.2 Industrial policies across all productivity structures

The results in Section 1.3.4 established that the form of optimal industrial policy depends critically on the productivity structure. When Harrod-neutral ($\iota = 0$), optimal policy consists of a constant ad-valorem wage subsidy to the targeted sector across all regions. When

productivity is Hicks-neutral ($\iota = 1$), optimal policy requires place-based subsidies per worker in the targeted sector that vary across regions based on underlying fundamentals.

The estimate of $\iota^* = 0.906$ suggests that English manufacturing is close to Hicks-neutral, implying that place-based policies should dominate uniform policies. However, this conclusion rests on a point estimate with inherent uncertainty. To provide robust policy guidance, I examine how both policy approaches perform across the entire range of possible productivity structures.

For values of $\iota \in [0, 1]$ that span the range, I implement the following procedure:

1. **Model inversion**: Re-invert the structural model to obtain a distribution of productivities and amenities consistent with the given ι, holding all other parameters fixed.

2. **Baseline equilibrium**: Solve for the competitive equilibrium with no industrial policy intervention.

3. **Policy implementation**: Implement two alternative industrial policies targeting the manufacturing sector to correct for agglomeration externalities ($\phi_m = 0.161$):

    - **Uniform policy**: Constant ad-valorem wage subsidy $s_m^* = \frac{\phi_m}{1+\phi_m} = 0.139$ across all regions to the manufacturing sector.
    - **Place-based policy**: Region-specific subsidy per worker $s_{im}^* = \phi_m \frac{p_{im}^* q_{im}^*}{L_{im}^*}$, where the subsidy varies with the optimal manufacturing revenue per worker in each region.

4. **Welfare calculation**: Compute the percentage change in aggregate welfare relative to the no-policy baseline for each policy approach.

This procedure generates a comprehensive comparison of policy effectiveness across all theoretically possible productivity structures, providing insights into the robustness of policy recommendations to uncertainty about the true value of ι. Figure 1.6 presents the main results of this analysis.

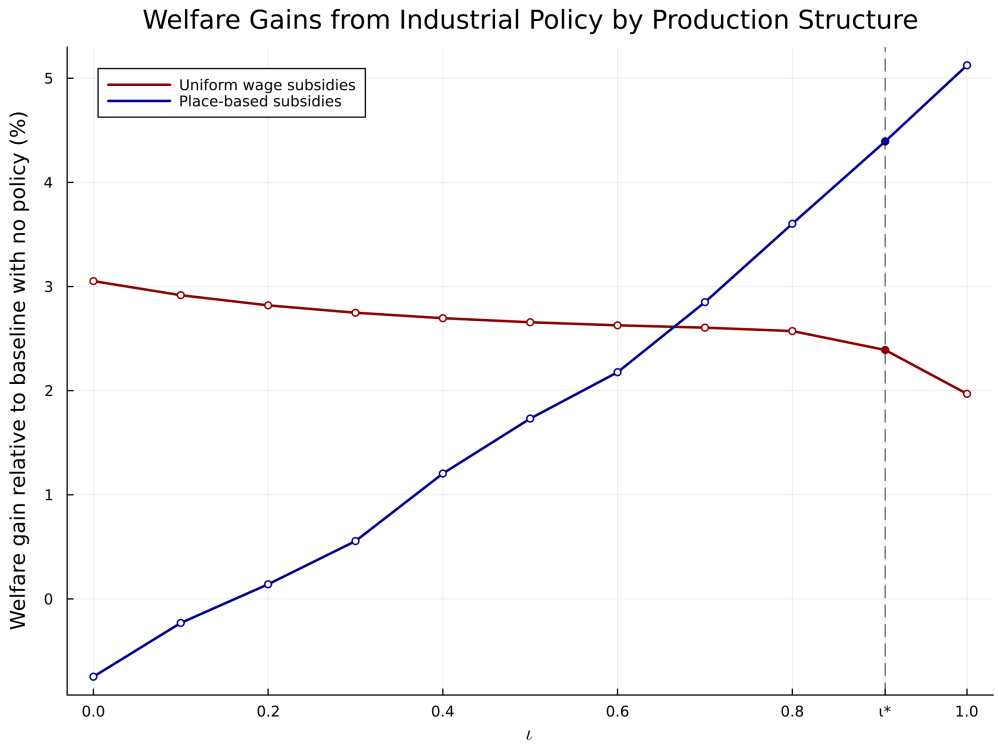


Figure 1.6: Red line represents welfare changes implementing a uniform wage subsidy, while the blue line represents welfare changes from a place-based subsidy. The vertical dotted line is the estimate for $\iota^* = 0.906$

The welfare implications reveal stark differences between the two policy approaches. Uniform wage subsidies generate relatively stable welfare gains that decline modestly as ι increases, from 3.01% under Harrod-neutral production to 2.4% at our estimated value of $\iota^* = 0.906$. This stability reflects that uniform policies partially correct the externality across all productivity structures by targeting wages, which always capture some component of the agglomeration benefit. When $\iota = 0$, the uniform wage subsidy is able to perfectly account for the agglomeration externality in each region by proportionally increasing wages by the right amount. However, as ι increases, the private marginal product of worker no longer captures the entire externality. In fact, the proportion of externality accounted for by the competitive wages decreases as we move towards Hicks-neutrality. However, since the marginal product of worker is always less than the average product, a wage subsidy never allocates more workers than optimal to the manufacturing sector and generates positive

welfare gains across all $\iota \in [0, 1]$ as discussed in section (1.3.5).

In contrast, place-based subsidies exhibit high volatility, generating welfare losses of nearly 0.7% when $\iota = 0$ but welfare gains of roughly 5% at our estimated value for ι^*. This arises because when $\iota = 0$, the place-based subsidy systematically over subsidizes all regions, particularly those with high revenue per worker, leading to excessive employment in manufacturing and welfare losses. As ι increases towards Hicks-neutrality, revenue per worker becomes the appropriate metric for the externality, and place-based subsidies begin to outperform uniform policies. The crossover point occurs around $\iota \in (0.6, 0.7)$, where both policies generate approximately equal welfare gains. For England's estimated productivity structure ($\iota^* = 0.906$), place-based policies clearly dominate, generating welfare gains about twice as large as uniform policies (5% vs 2.4%).

While place-based policies dominate for manufacturing in England, these results help generate important implications for industrial policy design more generally. Parameter uncertainty creates asymmetric policy risks. Determining optimal policy requires precise estimation of the productivity structure parameter ι, which may be infeasible in data sparse developing economies or emerging sectors. Moreover, implementing effective place-based subsidies requires detailed knowledge of regional fundamentals that are difficult to measure accurately. Estimation errors have asymmetric consequences. Incorrectly implementing place-based subsidies when production is closer to Harrod-neutral can generate welfare losses, while uniform subsidies provide a welfare floor regardless of the true productivity structure.

This analysis suggests a practical decision framework for policymakers. When facing high parameter uncertainty or limited administrative capacity, uniform wage subsidies represent the robust policy choice, requiring only knowledge of the agglomeration elasticity and guaranteeing modest welfare gains across all productivity structures. However, when policymakers can credibly estimate both ι and regional fundamentals as may be feasible in developed economies with rich data and institutional capacity, the potential gains from identifying the optimal policy design are substantial. They can potentially double the welfare benefits

relative to a standard uniform approach. The policy choice thus depends critically on the policymaker's informational environment and institutional capacity, not just the underlying economic structure.

1.6 Model extensions

1.6.1 Regional Agglomeration

First, I extend the framework to allow for agglomeration operating not only within sectors, but also at the regional level. Specifically, I modify the productivity term to depend on both sectoral and total employment. Namely,

$$z_{ik} = \bar{z}_{ik} L_{ik}^{\phi_k} L_i^{\phi}.$$

Under this environment, the misallocation of workers across sectors within a region remains formally identical to the baseline case without regional agglomeration. Consequently, the same set of industrial subsidies derived earlier continues to decentralize the planner's allocation and target sectoral externalities efficiently.

However, regional agglomeration introduces an additional channel of inefficiency through the allocation of workers *across* regions. When workers move to a region, the productivity of all sectors located there rises, yet this effect is not internalized in the competitive equilibrium. As a result, the planner requires additional instruments targeting the consumption per worker in each region. The optimal consumption per worker in each region is therefore given by

$$\tilde{P}_i c_i = \frac{\nu}{1+\nu}\left(\tilde{w}_i(1+(1-\iota)\phi) + \iota\phi y_i\right) + \Lambda,$$

where $y_i = \frac{\sum_k \tilde{p}_{ik} q_{ik}}{L_i}$ denotes total income per worker in region i.

The first term, $(1-\iota)\phi$, corresponds to the Harrod-neutral component of the regional

externality: it scales wages uniformly across all regions, functioning as a constant wage subsidy. The second term, $\iota\phi y_i$, represents the Hicks-neutral component: a place-based transfer proportional to regional income per capita. This transfer compensates for the aggregate productivity gains from expanding regional employment and parallels the logic in Fajgelbaum and Gaubert (2020) and Rossi-Hansberg et al. (2025).

Together, these components imply that when agglomeration operates at both regional and sectoral levels, optimal policy retains its industrial focus but must be complemented by policies that target consumption in each region through a uniform as well as a place-based component depending on the productivity structure.

1.6.2 Costly migration

Instead of workers being freely mobile across space, I now make migration costly for workers. I use the migration framework from Conte (2022). Each worker is endowed with a starting location $i \in \{1, \ldots, N\}$. Workers can then choose to stay in that region or move to any other region j subject to migration costs $\mu_{ij} > 0$. Workers continue to receive a fréchet preference shock ε with shape ν across all regions. A worker starting in any region i then solves:

$$\max_i \frac{v_i}{\mu_{ji}} \varepsilon_i,$$

which generates the following bilateral migration pattern:

$$\Pi_{ji} = \frac{\left(\frac{v_i}{\mu_{ji}}\right)^\nu}{\sum_n^N \left(\frac{v_n}{\mu_{jn}}\right)^\nu} L_j^0.$$

This implies that the equilibrium population in any given region is:

$$L_i = \sum_j \Pi_{ji} L_j^0.$$

Under such an environment, the misallocation across sectors within region remains the same, and as such can be targeted with the same set of instruments as in the case with no migration costs.

However, the result on optimal consumption per region gets vastly more complicated. First, the impact of congestion strength θ is heterogeneous across regions since regions face heterogeneous migration costs. As such, despite the fact that congestion cost on any region is the same across all regions, the planner weighs it differently since the cost of sending workers to any given region is different. This is a departure from our case with no migration costs. The optimal transfer to regions now depends on its migration costs since some regions could be far less accessible than others. Optimal consumption per region takes the following form:

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j W_j \frac{\Pi_{ji}}{L_i(1+\nu)} + \frac{\nu}{L_i(1+\nu)}\sum_j \psi_{ij}(P_j c_j - w_j) + \\ \frac{\nu\theta}{1+\nu}(\Gamma_i - \sum_j \psi_{ij}\Gamma_j) + \frac{\nu}{1+\nu}w_i = P_i c_i, \tag{1.19}$$

where α_j is the pareto weight for agents whose starting location is $j \in N$, $W_j = \left(\sum_j (\frac{a_j c_j}{\mu_{ij}})^{\nu}\right)^{1/\nu}$ is the expected welfare for an agent with starting location $j \in N$. Further,

$$\psi_{ij} = \sum_{n=1}^{N} \Pi_{ni}\frac{\Pi_{nj}}{L_n^0} \qquad\qquad \Gamma_i = \Gamma(\frac{\nu-1}{\nu})\frac{1}{L_i}\sum_j \alpha_j W_j \Pi_{ji}.$$

1.6.3 Heterogeneous Congestion

I now allow for the congestion externality to vary across regions. I write the amenities a_i in a region as

$$a_i = \bar{a}_i L_i^{-\theta_i},$$

where $\theta_i > 0$ is the congestion elasticity in region i. Under this environment, the misallocation of workers across sectors looks the same as in the case without agglomeration at a regional level. As such, the same set of industrial subsidies remain optimal to target the sectoral misallocation.

However, the results on optimal consumption per region change. Moving a worker across regions now has different marginal costs on account of congestion which no longer cancels out in the planner's allocation, which gets reflected in the consumption per worker for each region. This can be written as

$$\tilde{P}_i c_i = \frac{1}{1+\nu}\tilde{w}_i + \Lambda + R_i.$$

where

$$R_i = \frac{\nu}{1+\nu}\Gamma(\frac{\nu-1}{\nu})W\left(\sum_i \frac{L_i}{L}\theta_i - \theta_i\right).$$

As such, R_i is a regional transfers that depends on the strength of the congestion externality in a given region. Regions that have a higher congestion elasticity θ_i relative to other places receive a lower transfer, and vice versa.

1.7 Conclusion

The aim of this paper has been to examine the theoretical foundations for the recent global shift toward place-based industrial policies. I develop a framework showing that while region-sector agglomeration externalities are necessary for place-based interventions, they are not sufficient. The key insight is that the productivity structure determines optimal policy design. When agglomeration externalities affect Hicks-neutral productivity, optimal policy requires place-based subsidies that vary with regional fundamentals. On the other hand, when agglomeration externalities affect Harrod-neutral productivity, optimal policy is a uniform

ad-valorem wage subsidy to the targeted sector across all regions.

Using data on the manufacturing sector across 153 regions in England, I exploit variation on the input composition across regions to estimate ι and ϕ_m using a standard instrumental variable approach. I find $\iota^* = 0.906$ suggesting that manufacturing in England exhibits a predominantly Hicks-neutral structure. Further, I estimate $\phi_m = 0.161$ which provides evidence of substantial productivity spillovers. A 1% increase in the region sector's workforce is associated with a 0.161% increase in the productivity across all factors of production for that region-sector. These findings support place-based over uniform policies for England, and the optimal industrial policy mix increases welfare by 4.8%. However, sensitivity analysis reveals that place-based policies can reduce welfare when production structure is misidentified, while uniform policies consistently deliver positive welfare gains across all production structures.

These results highlight a fundamental tension in industrial policy design. Place-based policies offer large welfare gains when properly designed but require extensive information about regional fundamentals and carry significant downside risks from misimplementation. Uniform policies provide a more robust alternative, consistently delivering modest welfare improvements without requiring detailed knowledge of local economic conditions.

The framework I develop could additionally be used to think about other key policy questions in spatial, international trade, and macroeconomics. Policies aiming to correct for externalities that affect firm/industrial productivity such as innovation subsidies, trade subsidies, occupational subsidies, etc. can all be examined to see how productivity structure influences their optimal design. Further, the model could be augmented to include local frictions in land, labor, or other markets which better capture developing economy settings. Finally, the empirical setting could be extended by estimating agglomeration externalities across sectors to be able to use the model to identify sectors as well as regions for policy intervention.

As governments worldwide commit hundreds of billions to spatially targeted industrial interventions, this analysis offers what I hope is useful guidance for policy design. The choice

between place-based and uniform industrial policy should not rest merely on the presence of region-sector agglomeration externalities, but on a careful understanding of productivity structure, information constraints, and administrative capacity. When data and implementation capacity permit, estimating the productivity structure and accounting for regional fundamentals can deliver substantial welfare gains through spatially differentiated policies. Conversely, when productivity mechanisms are uncertain or state capacity is limited, uniform subsidies provide a robust safeguard—achieving meaningful improvements while avoiding costly misallocation from poorly targeted interventions. Ultimately, the design of industrial policy depends not only on recognizing the presence of region-sector agglomeration externalities, but on correctly understanding how technology shapes their transmission to output.

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Chapter 2

The Economic Geography of Climate Risk

Abstract

Projected temperature changes are variable in both their magnitude and geography. This paper studies how nonlinear damages and general equilibrium forces filter this climate risk across time and space. To do so, we build a tractable dynamic spatial model linking countries through trade and migration, and derive analytical first- and second-order welfare approximations that decompose the mean and variance of welfare changes into damage function, trade, and migration components. Using an ensemble of temperature projections from CMIP-6 and an empirically estimated damage function, we show that climate change-induced welfare risk is large. The standard deviation of country-level projected welfare loss across temperature projections is on average over 8% – compared to an average welfare loss of 13% – and is spatially unequal. Climate risk inequality is half as large as global income inequality. We show that spatial linkages reshape not only the level of climate damages, but also the spatial distribution of climate risk: accounting for trade and migration can reduce the standard deviation of welfare changes by up to 40% in low-income, internationally integrated nations that can diversify their exposure to local shocks.[12]

[12]Joint work with Jordan Rosenthal-Kay and Tom Bearpark.

2.1 Introduction

There is substantial uncertainty in both the path of global warming over the next century and its spatial distribution.[13] In a high-emissions scenario, state-of-the-art general circulation models (GCMs) from the CMIP-6 ensemble predict between 2 to 5.25°C of warming over populated areas depending on the model used, relative to 2019 (Figure 2.1, Panel A). However, temperature projections vary widely across regions, with some countries facing a much broader range of projected temperature outcomes across climate models than others (Figure 2.1, Panels B-D). In this paper, we study how nonlinear damages and the forces of economic geography filter this spatially uneven climate risk, and how accounting for climate risk affects the precision and mean estimates of the economic cost of climate change.

Statistical and economic models of climate damages imply nonlinear relationships between climate shocks and economic outcomes. Statistical models introduce damages that are nonlinear in weather shocks by estimating dynamically persistent state-dependent marginal effects in an environment where the state–average temperature–is itself time-varying. Economic models of climate change imply damages have nonlinear effects as agents are able to adapt to climate change. Because of these nonlinearities, differences in both the magnitude and variability of projected climate change can substantially affect the variance and point estimate of expected welfare. Moreover, since the extent of climate risk differs sharply across regions, accurately evaluating the welfare effects of climate change requires accounting for both the spatial distribution of climate risk and its spatiotemporal propagation. Regions have the potential to adapt to changes in climate through trade and migration, which connect them through the global goods and labor markets and shape how local shocks propagate across space.

[13] As emphasized by Knight (1921), uncertainty describes situations of ambiguity or ignorance about those probabilities themselves. In practice, we treat this intermodel uncertainty as *risk*: randomness with a known or estimable probability distribution. Our analysis concerns climate risk—the welfare implications of stochastic temperature shocks with empirically estimated distributions derived from global circulation models—rather than Knightian uncertainty over the true climate process.

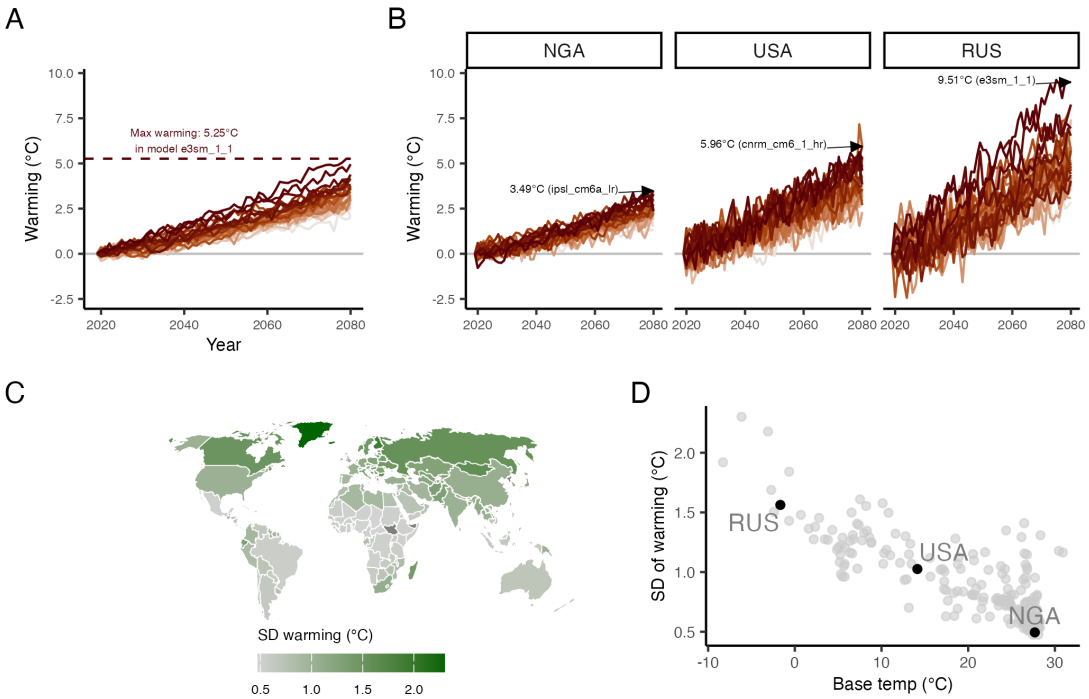


Figure 2.1: Projected warming across climate models.
Panel A shows the change in global population-weighted annual average near-surface temperature since 2019 across CMIP6 models under the SSP5–8.5 scenario. Panel B reports the corresponding changes in annual average temperature for selected countries. Panel C maps the spatial distribution of the standard deviation in projected warming by 2080 across CMIP models. Panel D plots the standard deviation of country-level warming across models as a function of baseline temperature, showing that colder countries tend to have greater variability in projected warming.

Existing literature has made substantial progress in understanding how these adaptation forces shape the cost of climate change (for reviews, see, e.g., Desmet and Rossi-Hansberg, 2024; Balboni and Shapiro, 2025). Dynamic spatial models show that trade and migration allow economies to adapt by reallocating activity toward cooler or more productive regions, while also propagating local shocks through goods and labor markets. We study how these forces shape climate *risk*: the variance of welfare outcomes under different climate projections. We ask two questions. First, how do global adaptation forces—trade and migration—affect the variance of welfare outcomes due to climate risk, and how do these mechanisms vary across countries? Second, how do nonlinear damages and their spatial

propagation influence the expected welfare costs of climate change, relative projections that evaluate welfare given a mean forecast of future temperature?

We find that general equilibrium forces have large and heterogeneous effects on welfare risk. In our simulations, the poorest and most globally integrated economies experience the largest gains from incorporating these adaptation margins. Trade and migration reduce the standard deviation in welfare changes by 2080 (under the SPS5-8.5 emissions trajectory) by as much as 40 percent. Access to foreign markets and migration opportunities allows these economies to diversify exposure to local climate shocks. By contrast, in relatively more closed economies, where domestic conditions dominate welfare fluctuations, trade and migration play a much smaller stabilizing role; instead, risk amplification and attenuation through the damage function dominate. This pattern mirrors their effect on average welfare costs: general equilibrium forces do not amplify damages but rather buffer them, allowing smaller economies to better absorb climate shocks through adaptation and reallocation. Together, these results show that global integration not only mitigates the expected cost of climate change but also redistributes and dampens the associated risk, generating substantial spatial heterogeneity in both the level and volatility of welfare losses.

A thorough quantitative analysis of the questions posed in this paper requires contributions along two key dimensions. First, we estimate a dynamic, non-linear damage function that maps changes in temperature into changes in model-implied productivity. This function anchors the link between physical climate shocks and the economic fundamentals of our model. We construct an annual panel of country-level data combining observed temperature realizations with model-implied productivity measures, and use it to estimate the causal relationships between temperature fluctuations and economic productivity. Following the climate impacts literature, we employ a flexible functional form that allows for non-linear and dynamic responses (Burke et al., 2015), building on recent approaches that trace the delayed effects of climate shocks on economic performance (Nath et al., 2024; Bilal and Känzig, 2024). Specifically, we incorporate distributed lags of temperature to capture ad-

justment dynamics over the subsequent decade. Because we estimate this relationship on a long panel, we are able to disentangle persistent effects weather shocks, while controlling for global trends and country fixed effects. This produces a rich empirical mapping from temperature to productivity that can be embedded directly into our quantitative model. Combining this estimated damage function with stochastic temperature projections from CMIP climate models enables us to simulate country-specific productivity distributions across temperature projections, and to propagate productivity shocks through the model's equilibrium to compute real income changes.

Second, we develop a tractable dynamic spatial model that links countries through trade and migration, which act as both margins of adaptation—allowing agents to adjust to local productivity shocks—and as mechanisms of propagation, transmitting weather shocks across space (via trade) and time (via migration). The model captures the key theoretical forces of adaptation and propagation while remaining analytically tractable and computationally efficient, allowing us to simulate numerous stochastic climate realizations and trace their welfare implications globally.

Within this environment, we derive a first-order welfare approximation (reminiscent of the results in Kleinman et al., 2024a; Kleinman et al., 2024b) for welfare changes induced by small productivity shocks that incorporates general equilibrium feedback, decomposed according to the contribution of direct impacts (i.e., through the damage function) versus those coming through trade and migration. We then extend this to a second-order approximation that captures curvature in the welfare function arising from nonlinear damages and higher-order GE effects. These results yield a set of transparent analytical decompositions that separate welfare changes into direct, trade, and migration components—each of which can be computed empirically and compared across countries.

This framework allows us to trace how the impact of climate shocks accumulates over time and how adaptation and propagation interact to shape the distribution of welfare risk. Using country-specific temperature projections from the CMIP ensemble, we simulate global

welfare trajectories and decompose them into their underlying channels. Together, these elements provide a unified, empirically grounded framework that connects climate projection variability to the geography of welfare risk.

We then use our framework to decompose both the expected cost and the variance of welfare into direct and general equilibrium (GE) components for every country in the world. GE forces have highly heterogeneous implications for welfare. In much of sub-Saharan Africa and South and Southeast Asia, trade and migration attenuate direct welfare losses by reallocating resources toward less-affected regions. In other areas, GE forces can instead exacerbate losses through adverse terms-of-trade effects—when local productivity declines relative to trading partners—or through migration inflows and outflows that redistribute exposure to shocks. These contrasting channels generate substantial spatial heterogeneity in the global geography of climate costs.

When we turn to welfare variance, we find that GE forces dampen volatility nearly everywhere, but with sharp cross-country differences. Countries that are highly integrated in global trade experience the largest stabilizing gains, with welfare variance falling by up to 25 percent in some smaller economies such as Chad and Greece. In contrast, for larger economies such as the United States or Russia, GE channels have little effect on welfare volatility because domestic shocks dominate. These results carry clear policy implications: openness to trade and migration provides a form of insurance against local climate shocks, helping to stabilize welfare under climate risk.

Related literature A large body of research has used reduced-form estimates of the causal relationship between temperature and GDP to project the global economic consequences of climate change (see Hsiang, 2025; Lemoine et al., 2025, for recent reviews). This literature consistently finds a non-linear relationship between temperature and output (Burke et al., 2015; Kalkuhl and Wenz, 2020; Nath et al., 2024): warming tends to raise productivity in cold countries but reduce it in hot ones, with most studies identifying an optimal average temperature of around 14°C. Studies differ on persistence: while Burke et al. (2015) link tem-

perature to GDP growth—implying compounding long-run effects—others argue that only changes in temperature affect growth, with impacts that can persist for a decade or more (Nath et al., 2024; Bilal and Känzig, 2024). In this paper, we adopt an estimation strategy that accommodates both non-linear impacts and persistent—but not permanent—effects of a sustained change in temperature.

A central challenge in this literature is the large variance surrounding projected economic damages from climate change (Newell et al., 2021). For instance, Burke et al. (2015) report a 95% confidence interval for global GDP losses by 2100 that ranges from –60% to +50%. Importantly, this wide range reflects only statistical uncertainty in the estimated damage function, neglecting the role of climate risk. Subsequent work—often outside the core GDP–climate literature—has expanded this analysis to include uncertainty about the future climate, typically by bootstrapping damage estimates across ensembles of climate model realizations. For example, Carleton et al. (2022) account for both damage-function and climate risk in their projections of climate-induced mortality, finding that the two sources contribute roughly equally to variance in 2100 outcomes. Similarly, Burke et al. (2023) show that uncertainty in future climate trajectories adds a comparable magnitude of uncertainty to Social Cost of Carbon calculations to that arising from estimation of the damage function. A smaller emerging literature decomposes other sources of uncertainty in projected impacts: Schwarzwald and Lenssen (2022) highlights the role of internal climate variability—differences across realizations within a single climate model—which we do not explicitly analyze in this paper.

A key limitation of these reduced form studies is that they treat economies as spatially isolated, neglecting how economic geography forces both create spatial spillovers but also the ability for local adaptation through trade and migration. As GDP is itself an endogenous outcome influenced by cross-border interactions, omitting these spatial linkages may overstate projected welfare damages and their variance, and obscure how global adaptation could redistribute and reduce climate risk (Zappala, 2024; Bilal and Känzig, 2024).

This paper contributes to the growing literature on how trade and migration shape the welfare consequences of climate change. Recent research has expanded classic integrated assessment models (IAMs) to capture spatial heterogeneity, trade, and migration, giving rise to spatial integrated assessment models (S-IAMs) that examine how geography influences both the level and distribution of climate damages. Desmet and Rossi-Hansberg (2015) formalized dynamic spatial equilibrium frameworks showing that spatial frictions—especially in trade and migration—critically determine aggregate and local climate costs. Subsequent research has broadened this agenda along several dimensions. Desmet et al. (2021) evaluate probabilistic projections of local sea-level rise in a dynamic spatial model. Conte et al. (2021) study how warming reshapes global patterns of industrial specialization, while Cruz and Rossi-Hansberg (2024) develop a global S-IAM with endogenous migration, innovation, and demographic dynamics. Balboni (2025) and Rudik et al. (2022) analyze temperature and flooding impacts in models with forward-looking migration, and Krusell and Smith Jr (2022) emphasize forward-looking investment and savings as alternative adaptation channels. Bilal and Rossi-Hansberg (2023) highlight how anticipation of extreme events, spatial capital adjustment, and externalities affect long-run outcomes. Dingel and Meng (2025) show that spatially correlated temperature shocks can amplify inequality by altering the gains from trade. The interaction between environmental policy and geography has also been explored (Acemoglu et al., 2016; Conte et al., Forthcoming).

Despite these advances, most dynamic spatial analyses evaluate deterministic climate scenarios, abstracting from variability across temperature paths. A notable exception is Desmet et al. (2021), who examine heterogeneous flooding risks under alternative Representative Concentration Pathways (RCPs). In contrast, we incorporate stochastic temperature dynamics into a spatial general equilibrium framework with trade and migration. Importantly, we derive analytical first- and second-order welfare decompositions that isolate how both the estimated damage function and general equilibrium forces shape both the level and variance of welfare under climate risk across time and space.

Finally, this paper is also related to recent work that develops decompositions of welfare exposure to shocks in quantitative spatial models. Kleinman et al. (2024a) derive 'friend–enemy' matrices that characterize the first-order elasticity of real income to productivity changes across countries in a trade model. Kleinman et al. (2024b) and Donald et al. (2025) extend these sufficient statistics to spatial settings with migration. We build on this linear-exposure logic but go further by deriving both first- and second-order welfare approximations that quantify not only the expected welfare cost but also the variance and curvature components arising from adaptation and propagation. This allows us to isolate how trade and migration separately shape both the mean and dispersion of welfare impacts across regions.

2.2 Model

In this section, we develop a simple dynamic spatial equilibrium model in which countries are linked through trade and migration. The model provides a tractable framework to study how shocks to fundamentals propagate across time and space through these two margins of adjustment. The environment extends the canonical Armington (Anderson, 1979) structure to a dynamic setting in which agents' migration decisions generate intertemporal spillovers. The world is populated by measure $\bar{L}$ workers dispersed across all countries, each of whom is endowed with one unit of labor that they supply inelastically to their nation's final goods firm. There are N countries indexed by $o, d \in \{1, \ldots, N\}$. Time is discrete and indexed by t. The timing within each period is as follows:

1. Workers 'wake up' in origin country o at the beginning of period t, and make a one-period ahead migration decision to destination country d.

2. Populations update according to realized migration decisions.

3. Production, trade, and consumption take place in each destination.

Workers migrate across regions paying a bilateral migration cost μ_{od} expressed in terms of utility. Trade is costly and subject to standard iceberg trading costs τ_{od}, and there is no ability for agents to save.

2.2.1 Workers

Utility and Consumption. Conditional on being in a country d, workers supply one unit of labor inelastically to the country's representative firm and earn wage $w_{d,t}$. They consume a basket of goods sourced from nations o, and have CES preferences over national varieties, and enjoy country-specific amenities $A_{d,t}$. The value of residing in country d is given by

$$V_{d,t} = \max_{\{C_{od,t}\}} A_{d,t} \left(\sum_o C_{od,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad \text{subject to } \sum_o p_{od,t} C_{od,t} \leq w_{d,t},$$

where $p_{od,t} = \tau_{od} p_{o,t}$ is the price of the variety from country o adjusted for the iceberg trading cost between countries. Expenditure minimization implies the standard CES price index

$$P_{d,t} = \left(\sum_o p_{od,t}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

Demand for each imported variety can be written as

$$C_{od,t} = \left(\frac{p_{od,t}}{P_{d,t}} \right)^{-\sigma} \frac{w_{d,t}}{P_{d,t}}. \tag{2.20}$$

Migration. In each period t, there is a continuum of workers indexed by ω residing in origin o of measure $L_{o,t-1}$. Each worker decides where to live and work in period t. Workers draw idiosyncratic preference shocks $\epsilon_{od}(\omega)$ that are distributed Fréchet $(1, \varepsilon)$ iid across countries. Each worker solves

$$\max_d \left\{ \frac{V_{dt}}{\mu_{od}} \epsilon_{odt}(\omega) \right\}, \tag{2.21}$$

where μ_{od} captures bilateral migration costs of moving from o to d. The resulting migration probabilities of moving from o to d satisfy

$$M_{od,t} = \frac{(V_{d,t}/\mu_{od})^{\varepsilon}}{\sum_{d'}(V_{d',t}/\mu_{od'})^{\varepsilon}}, \tag{2.22}$$

and ex–ante expected welfare for workers in o is

$$\mathcal{W}_{ot} \propto \left(\sum_{d}(V_{dt}/\mu_{od})^{\varepsilon}\right)^{1/\varepsilon}. \tag{2.23}$$

2.2.2 Technology and Firms

Each country produces a differentiated Armington variety using labor as the only factor of production. The representative firm in country d has linear technology using productivity $Z_{d,t}$,

$$Y_{d,t} = Z_{d,t}L_{d,t}.$$

Perfectly competitive firms take wages $w_{d,t}$ and prices $p_{d,t}$ as given, and solve

$$\max_{L_{d,t}} \; p_{d,t}Z_{d,t}L_{d,t} - w_{d,t}L_{d,t}.$$

Since labor is the only factor, wages equal the value of marginal product such that

$$w_{d,t} = p_{d,t}Z_{d,t}. \tag{2.24}$$

2.2.3 Market Clearing

Output market clearing requires that total production equals global demand for each variety such that

$$Y_{o,t} = \sum_d \tau_{od} C_{od,t} L_{d,t}. \tag{2.25}$$

The aggregate labor market must also clear. The initial population distribution is such that $\sum_o L_{o,0} = \bar{L}$, and there is no population growth. Given migration probabilities in (2.22), the population in each country evolves according to

$$L_{d,t} = \sum_o M_{od,t} L_{o,t-1}. \tag{2.26}$$

2.2.4 Equilibrium

We are now ready to define the notion of equilibrium. We first define a period-t specific equilibrium, before defining a dynamic equilibrium.

Definition 2.2.1 (Period-t Equilibrium)**.** Given fundamentals $\{A_{o,t}, Z_{o,t}\}$, elasticities (ε, σ), iceberg trade costs $\{\tau_{od}\}$, and initial populations $\{L_{o,t-1}\}$, a period-t equilibrium is a set of wages $\{w_{o,t}\}$, prices $\{p_{o,t}\}$, consumption $c_{od,t}$, and population distribution $\{L_{o,t}\}$ such that:

1. Workers choose consumption optimally, satisfying equation (2.20).
2. Firms choose labor inputs to maximize profits, and wages satisfy equation (2.24).
3. Goods markets clear, satisfying equation (2.25).
4. The population distribution across countries satisfies equation (2.26).

Definition 2.2.2 (Dynamic Equilibrium)**.** Given sequences of fundamentals $\{A_{o,t}, Z_{o,t}\}_{t=0}^{\infty}$ and an initial population distribution $\{L_{o,0}\}$, a dynamic equilibrium is a sequence

$\{p_{o,t}, w_{o,t}, L_{o,t}\}_{t=0}^{\infty}$ such that each period t constitutes a period-t equilibrium and the population evolves according to (2.26).

A stationary equilibrium corresponds to a population distribution in which $L_{o,t} = L_{o,t-1}$ for all i.[14]

2.2.5 Discussion

The model captures how spatial adjustment to shocks unfolds through contemporaneous trade and migration decisions. Each period's allocation reflects current fundamentals: workers respond to observed wages, prices, and amenities. This static behavior generates a dynamic sequence of equilibria through the law of motion for populations—today's realized distribution of workers $\{L_{o,t}\}$ becomes tomorrow's inherited state.

Under this formulation, persistence in spatial outcomes arises from the gradual reallocation of workers across space. Shocks to fundamentals—such as changes in productivity, amenities, or climate—affect wages and prices contemporaneously, leading to new migration flows that redefine the distribution of population in subsequent periods. Trade linkages transmit these shocks across locations within a period, while migration links outcomes across periods.

2.3 Welfare decomposition

This section summarizes how trade and migration shape the propagation of shocks into welfare. We build four components: (i) a first–order welfare decomposition for productivity shocks; (ii) an analogous result for (initial) population shocks; (iii) a dynamic accumulation result that organizes propagation over time; and (iv) variance and Jensen (curvature) decompositions that map uncertainty in fundamentals into uncertainty in welfare.

[14] That is, the equilibrium population vector is proportional to the dominant eigenvector of the migration matrix $\mathbf{M}_t$.

We let $\mathcal{W}_{o,t}$ denote *ex ante* welfare for agents starting period t in country o. This is the welfare for agents before they receive idiosyncratic location specific preference shocks. Defining indirect utility as $V_{o,t} = A_{o,t}\frac{w_{o,t}}{P_{o,t}} \quad \forall o$, (i.e, amenity-adjusted real income), country level welfare $\mathcal{W}_{o,t}$ takes the following form:[15]

$$\mathcal{W}_{o,t} \;=\; V_{o,t}\left(\sum_{d}\mu_{od}^{-\varepsilon}\left(\frac{V_{d,t}}{V_{o,t}}\right)^{\varepsilon}\right)^{1/\varepsilon}. \tag{2.28}$$

2.3.1 First–order welfare impact of productivity shocks

We consider the effect, within period t, of a small productivity shocks $d\ln Z_t$ and initial population shocks $d\ln L_{t-1}$ on period-t welfare for any country. Absent productivity shocks, there is mechanical convergence to the steady state so that $d\ln L_{t-1}$ is nonzero.

The following proposition decomposes the first order changes to welfare as a consequence to shocks in productivity and starting population.

Proposition 2.3.1 (First–order decomposition)**.** *In any period-t equilibrium, the first-order change in the log welfare for any country $o \in \{1,\cdots,N\}$ can be written as,*

$$d\ln \mathcal{W}_t = (\mathbf{I} + \boldsymbol{\mathcal{T}}_{t-1} + \boldsymbol{\mathcal{M}}_{t-1})\, d\ln Z_t + \mathcal{L}_t. \tag{2.29}$$

where $d\ln Z_t$ is an N-dimensional vector of productivity shocks.

Proof. See Appendix (B2.1). □

We refer to $\mathbf{I}\; d\ln Z_t$ as the direct, or damage function effect, $\boldsymbol{\mathcal{T}}_{t-1}\; d\ln Z$ as the trade effect, and $\boldsymbol{\mathcal{M}}_{t-1}\; d\ln Z_t + \mathcal{L}_t$ as the migration effect. These matrices are functions of trade,

[15] When we discuss global welfare in any period t, we adopt a utilitarian aggregator. Namely,

$$\Upsilon_t \;=\; \sum_{o} L_{o,t}\,\mathcal{W}_{o,t}, \tag{2.27}$$

income, and migration shares. Dropping time subscripting, the trade effect is given by,

$$\boldsymbol{\mathcal{T}} = (\mathbf{I} - \mathbf{T}^\top)\mathbf{A}^Z$$

while the migration multiplier on the shock is,

$$\boldsymbol{\mathcal{M}} = \underbrace{(\mathbf{M} - \mathbf{I})\mathbf{A}^Z}_{\text{migration option}} + \underbrace{(\mathbf{M} - \mathbf{I})(\mathbf{I} - \mathbf{T}^\top)\mathbf{A}^Z}_{\text{trade-migration interaction}}$$

where the matrices $\mathbf{T}$ is the trade share matrix, and $\mathbf{M}$ is the migration matrices; i.e.,

$$\mathbf{T}_{od} = \left(\frac{\tau_{od}\, p_o}{P_d}\right)^{1-\sigma}, \qquad \mathbf{M}_{od} = \left(\frac{V_d/\mu_{od}}{\mathcal{W}_o}\right)^{\varepsilon},$$

and $\mathbf{A}^Z$ maps productivity shocks into prices changes ($d\ln p = \mathbf{A}^Z\, d\ln Z$). Further,

$$\mathcal{L}_t = \mathbf{M}(I - \mathbf{T}^\top)\mathbf{A}^L\; d\ln L,$$

where $\mathbf{A}^L$ maps initial-population shocks into price changes ($d\ln p = \mathbf{A}^L\, d\ln L^0$). Both $\mathbf{A}$-operators depend on primitives and statistics of the state (the spatial distribution of population and productivity).[16] The decomposition illustrates how shocks to fundamental productivity interact with the forces of economic geography to shape welfare outcomes.

The **direct effect**, $d\ln Z_t$ is read off the damage function. A local productivity shock im-

[16]The relevant statistics of the state are given by the matrices $(\mathbf{L}, \mathbf{M}, \mathbf{T}, \mathbf{S})$. Defining,

$$\mathbf{Q} = \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S} - \mathbf{I})$$

to be the pass-through matrix of endowment shocks to prices, where $\mathbf{S}_{od} = \mathbf{T}_{od}\frac{w_d L_d}{w_o L_o}$, the price effect in our model with migration is,

$$\mathbf{A}^Z = \left(\mathbf{I} - \mathbf{Q}\epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})(\mathbf{I} - \mathbf{T}^\top)\right)^{-1}\mathbf{Q}\left(\mathbf{I} + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})\right)$$

and prices respond to population shocks according to,

$$\mathbf{A}^L = (\mathbf{I} - \mathbf{Q})^{-1}\mathbf{Q}\mathbf{L}^\top$$

where $\mathbf{L}_{od}$ is the share of persons in destination d who originated in o.

mediately changes real income in the affected region, holding prices and migration patterns fixed. The **trade effect** captures how terms of trade adjust to the full vector of productivity shocks. Through international trade, each region's welfare depends its productivity relative to those of its trading partners. All else equal, negative productivity shocks can improve a nation's terms-of-trade as the price of its export appreciates, changing real consumption possibilities. This is the mechanism through which trade acts as a form of adaptation. Quantitatively, the strength of this adaptation mechanism depends on how a nation's productivity changes relative to those its trading partners.

The term captures the **migration option effect**. As agents can relocate across regions, a productivity shock elsewhere changes the relative attractiveness of destinations. Agents who stay enjoy real income changes from emigration, and a positively selected on their preference shock. For residents of origin o, higher productivity in d increases the option value of migrating there, even if they ultimately stay, since equilibrium migration probabilities M_{od} depend on relative utilities across all destinations. The fourth term represents the **interaction effect between trade and migration**. Conditional on migration responses, changes in productivity elsewhere alter both where individuals move and how potential migration destinations' terms-of-trade adjust. Thus, the gains from mobility depend not only on the dispersion of productivities but also on the geography of trade costs and price adjustment across destinations. Finally, the term $\mathcal{L}_t$ in the decomposition captures welfare gains from the population distribution converging towards the steady state.

Using this decomposition, we can trace how the effects of productivity shocks accumulate over time.

$$\begin{aligned}\ln \mathcal{W}_t - \ln \mathcal{W}_0 &\approx \sum_{n=1}^{t} d \ln \mathcal{W}_n \\ &= \sum_{n=1}^{t} \left(\mathbf{I} + \boldsymbol{\mathcal{T}}_{n-1} + \boldsymbol{\mathcal{M}}_{n-1}\right) d \ln Z_n + \mathcal{L}_t,\end{aligned}$$

where $\boldsymbol{\mathcal{T}}_{n-1}$ captures the propagation of shocks through trade at time n, $\boldsymbol{\mathcal{M}}_{n-1}$ captures

migration and migration–trade interaction effects, and $\mathcal{L}_t$ summarizes the population convergence effect.

This expression emphasizes that the total welfare change at any date reflects the cumulative history of productivity shocks weighted by the structure of trade and migration linkages in previous periods. Trade linkages propagate shocks contemporaneously across space, while migration linkages propagate them intertemporally across periods. The term $\mathcal{L}_t$ captures additional adjustment arising from gradual reallocation of population, which can either amplify or dampen past shocks depending on how migration reshapes exposure to productivity across space.

2.3.2 Welfare curvature: second order effects

We now investigate the curvature of the welfare function, which shapes how general equilibrium forces can amplify or attenuate climate risk. Moreover, the second derivative of the welfare function informs us about the magnitude of the correction we must make to the expected welfare loss when integrating over the distribution of future climate, instead of evaluating welfare along the mean trajectory.

Within a given period t, the second–order response of welfare to productivity shocks $d \ln Z_t$ is given by the following proposition.

Proposition 2.3.2 (Second–order welfare decomposition)**.** *In any period–t equilibrium, the second–order change in log welfare for any country $o \in \{1, \dots, N\}$ is*

$$d^2 \ln \mathcal{W}_o = \underbrace{(\sigma - 1)\ Var_{\mathbf{T}_{\cdot d}}(d \ln p_o)}_{\textit{trade adaptation}} + \underbrace{\varepsilon\ Var_{\mathbf{M}_{o\cdot}}(d \ln V_d / V_o)}_{\textit{migration adaptation}} + \underbrace{\sum_{od} M_{od}\Big(d^2 \ln V_d / V_o\Big) - \sum_{o} \mathbf{T}_{od}\Big(d^2 \ln p_o / p_d\Big)}_{\textit{second–order price effects}}.$$

Proof. See Appendix B2.4. □

Standard spatial models often evaluate welfare at the expected path of fundamentals, computing $\ln \mathcal{W}(\mathbb{E}[Z_t])$. However, when welfare is nonlinear in productivity—as is the case once trade and migration linkages create convexities—the expected welfare loss across climate realizations, $\mathbb{E}[\ln \mathcal{W}_t]$, can differ substantially from the welfare computed at expected fundamentals. This distinction follows from Jensen's inequality, which states that for any function $f(\cdot)$ and random variable x, $f(\mathbb{E}[x]) \gtrless \mathbb{E}[f(x)]$ depending on whether $f(\cdot)$ is either convex or concave. Applied to welfare, this implies that the bias from failing to account for climate risk depends on,

$$\mathbb{E}_k \left[d \ln \mathcal{W}_t^{(k)} \right] - d \ln \mathcal{W}_t \left(\mathbb{E}_k [d \ln Z_t] \right) \approx \frac{1}{2} d^2 \ln \mathcal{W}_t \times \text{Var} \left(d \ln Z_t^{(k)} \right)$$

depends on whether welfare is locally convex or concave in productivity. In our context, we are interested in what drives the difference between these two objects. We can use the second–order decomposition of welfare to characterize the shape of this relationship.

The second–order terms capture how dispersion in local prices and migration returns translates into curvature in welfare. **Trade adaptation** makes the welfare function more convex: when productivity shocks induce price dispersion across trading partners, trade allows countries to substitute toward cheaper imports, raising welfare through within–period reallocation. A higher elasticity of substitution (σ) amplifies this effect, reflecting stronger risk–sharing and a greater capacity to smooth localized shocks. **Migration adaptation** parallels this mechanism across space. When migration frictions are low (high ε), workers can reallocate toward destinations where real incomes rise, yielding welfare gains from the cross–sectional variance in destination–specific returns.

Taken together, trade and migration adaptation make the welfare function more nonlinear in fundamentals: by linking regions through prices and mobility, they transform local shocks into convex welfare responses. Finally, the residual term captures higher–order general–equilibrium effects that reflect feedback from expenditure and labor reallocation into

local prices. Together, these components quantify how the economy's spatial margins of adjustment shape not only the mean but also the volatility and curvature of welfare responses to shocks.

2.3.3 Mean effects and variance decomposition

This framework allows us to decompose the sources of welfare change into their underlying propagation channels. For a sequence of shocks $\{d \ln Z_t^{(k)}\}$—along a certain simulated climate or productivity paths (k)—the contribution of each channel to cumulative welfare changes can be written as:

$$\begin{aligned}
\text{Direct role}_t^{(k)} &= \frac{\sum_{n=1}^{t} d \ln Z_n^{(k)}}{\ln \mathcal{W}_t - \ln \mathcal{W}_0}, \\
\text{Trade role}_t^{(k)} &= \frac{\sum_{n=1}^{t} \boldsymbol{\mathcal{T}}_{n-1} d \ln Z_n^{(k)}}{\ln \mathcal{W}_t - \ln \mathcal{W}_0}, \\
\text{Migration role}_t^{(k)} &= \frac{\sum_{n=1}^{t} \boldsymbol{\mathcal{M}}_{n-1} d \ln Z_n^{(k)} + \hat{\mathcal{L}}_t}{\ln \mathcal{W}_t - \ln \mathcal{W}_0}.
\end{aligned}$$

These expressions quantify the relative importance of each mechanism in shaping cumulative welfare changes. The direct term isolates the effect of own-country productivity shocks. The trade term measures how exposure through import and export linkages transmits foreign shocks. The migration term captures how the reallocation of workers, together with induced changes in population weights and option values (the $\hat{\mathcal{L}}_t$ component), contributes to global adjustment.

Having established how trade and migration shape the mean response of welfare to shocks, we now examine how they affect the *variance* of welfare across climate realizations (k). For each time t, we decompose the contribution of direct, trade, and migration channels to the

cross–chain variance of welfare as

$$\begin{aligned}
\text{Direct Share}_t &= \frac{\text{Var}_k\left(\sum_{n=1}^{t} d\ln Z_n^{(k)}\right)}{\text{Var}_k(\ln \mathcal{W}_t - \ln \mathcal{W}_0)}, \\
\text{Trade Share}_t &= \frac{\text{Var}_k\left(\sum_{n=1}^{t} (\mathbf{I} + \boldsymbol{\mathcal{T}}_{n-1}^{(k)})\, d\ln Z_n^{(k)}\right) - \text{Var}_k\left(\sum_{n=1}^{t} d\ln Z_n^{(k)}\right)}{\text{Var}_k(\ln \mathcal{W}_t - \ln \mathcal{W}_0)}, \\
\text{Migration Share}_t &= \frac{\text{Var}_k\left(\sum_{n=1}^{t} (\mathbf{I} + \boldsymbol{\mathcal{M}}_{n-1}^{(k)})\, d\ln Z_n^{(k)}\right) - \text{Var}_k\left(\sum_{n=1}^{t} d\ln Z_n^{(k)}\right)}{\text{Var}_k(\ln \mathcal{W}_t - \ln \mathcal{W}_0)}.
\end{aligned}$$

The residual share captures interaction effects and the covariance structure arising from serial and spatial autocorrelations.

The **direct share** measures the portion of welfare variance that would arise in the absence of any trade or migration responses—that is, the propagation of uncertainty purely through shocks to local productivity. In isolation, this accounts for all variance in a world of autarky and immobile labor.

Trade and migration, by contrast, reshape how uncertainty transmits across space. Trade connects countries through their price indices: if a volatile region trades with more stable partners, international trade smooths welfare by diversifying consumption baskets and dampening local volatility. Conversely, when a stable region trades extensively with highly uncertain partners, it imports volatility through fluctuations in foreign prices.

Migration operates analogously through the reallocation of workers. When migration frictions are low, workers can relocate away from volatile or adversely affected regions toward more stable ones, attenuating welfare dispersion. However, when migration primarily links countries with correlated or volatile fundamentals, mobility can instead transmit instability across borders.

As such, whether the forces of economic geography in trade and migration amplify or attenuate welfare variance is ultimately an empirical question.

2.4 Estimation

2.4.1 Data

GDP data We obtain estimates of GDP per capita (GDP-PC) from the World Bank's *World Development indicators* (WDI) database, expressed in constant 2015 US dollars. These data have been widely used in studies that project the GDP consequences of climate change (e.g., Burke et al., 2015; Nath et al., 2024). Our dataset forms an unbalanced panel covering the period 1960–2019; we exclude observations beyond 2019 to avoid distortions associated with the COVID-19 pandemic. Among the 199 countries in the dataset, 87 have complete GDP-PC coverage for the entire 1960–2019 period, while the remaining countries exhibit missing values in early years (see Appendix Figure B1 for details on data availability by country). The WDI also provides us with country-year level population estimates.

Historical temperatures We match these GDP data with temperature data obtained from the ERA5 dataset (Muñoz-Sabater et al., 2021). ERA5 provides daily, grid-cell level temperature and precipitation estimates, which we population weight using gridded population estimates, before aggregating to the country-year level.[17]

Trade and migration data We use bilateral trade flows, expressed in nominal dollars, for years 2000-2016 from the U.S. Gravity Portal (Gurevich and Herman, 2018). For historical bilateral migration flows, we rely on those from Abel and Cohen (2022), who use demographic accounting methods to recover bilateral migration flows in 1990,1995,2005, and 2010.

CMIP projections We use 35 CMIP-6 projections for the RCP 8.5 forcing scenario made available through the Copernicus website.[18] We aggregate CMIP-6 projections to the country level by population-weighting gridcell level estimates.[19]

[17]Populations weights are time invariant, and calculated using the Gridded Population fo the World dataset, available here: https://sedac.ciesin.columbia.edu/data/collection/gpw-v4

[18]See: https://cds.climate.copernicus.eu/datasets/projections-cmip6.

[19]We note that CMIPs reflect 'ensembles of opportunity' (Rasmussen et al., 2016): they are sampled from

2.4.2 Model estimation and calibration

We set $\sigma - 1 = 4$ following Simonovska and Waugh (2014) and set $\epsilon = 2$ following Cruz and Rossi-Hansberg (2024).

Estimating spatial frictions To estimate τ_{od} and μ_{od}, we follow the 'covariates-based approach' of Dingel and Tintelnot (2025). That is, we parameterize our spatial frictions as a function of covariates. We do this to avoid overfitting estimates of τ_{od} and μ_{od} on noisy trade and migration flows Many trade and migration flows in the data are zero. Subsequently, fitting trade and migration costs to exactly rationalize historical flows as a model equilibrium would generate infinite trade or migration costs for some country pairs. By smoothing the data with a low rank approximation to the trade and migration costs, we allow for trade and migration flows to occur in counterfactuals that are not seen in historical data.

To estimate our spatial frictions, we use the model's gravity regressions for trade and migration flows,

$$\begin{aligned} \mathbf{M}_{odt} &= \exp\left(-\epsilon \ln \mu_{odt} + \xi_{ot} + \xi_{dt}\right) \\ \mathbf{T}_{odt} &= \exp\left(-(\sigma - 1) \ln \tau_{odt} + \chi_{ot} + \chi_{dt}\right) \end{aligned} \tag{2.30}$$

We treat these as estimating equations in which we suppose $\mu_{odt}^{-\epsilon} = \exp(\Gamma X_{od}) u_{odt}$ and $\tau_{odt}^{1-\sigma} = \exp(\Lambda X_{od}) v_{odt}$ where $\mathbb{E}\left[u_{odt} \mid \xi_{ot}, \xi_{dt}, X_{od}\right] = \mathbb{E}\left[v_{odt} \mid \xi_{ot}, \xi_{dt}, X_{od}\right] = 1$. This allows us to exchange $\tau_{odt}^{1-\sigma}$ and $\mu_{odt}^{-\epsilon}$ for $\exp(\Gamma X_{od})$ and $\exp(\Lambda X_{od})$ and estimate Equations (2.30) using a Poisson pseudo-maximum likelihood estimator with high-dimensional fixed effects (Silva and Tenreyro, 2006; Correia et al., 2020).[20] Inside X_{od} we use the standard gravity regressors: log distance, and indicators for colonial history, legal and linguistic similarities,

participating GCMs and do not align with less granular forecasts like MAGICC (Model for the Assessment of Greenhouse Gas Induced Climate Change, a 'simple' GCM). One approach to align granular CMIP uncertainty with estimates of aggregate uncertainty is to develop surrogate models by resampling from the CMIP distribution (as in Carleton et al., 2022; Tran-Anh and Ngo-Duc, 2024) or estimating and drawing from the CMIP DGP, which we aim to do in future work.

[20] We enforce $\tau_{oo} = \mu_{oo} = 1$ by including $1(o = d)$ as a regressor in X_{od} and rescaling all elements of $\hat{\Gamma}$ and $\hat{\Lambda}$ accordingly.

and contiguity (Gurevich and Herman, 2018). Estimation results are available in Table B1.

Estimating the damage function We invert the model using our GDP and population data to recover Z_{ot} for each country-year in the data. [21] To estimate damages, we run regressions of the form,

$$\Delta \log Z_{ot} = \sum_{\ell=0}^{L} \beta_{0,\ell} \Delta C_{o,t-\ell} + \beta_{1,\ell} \Delta (C_{o,t-\ell})^2 + \eta_o + \eta_t + \delta_o \cdot t + e_{ot} \tag{2.31}$$

where $C_{i,t}$ is temperature and Δ first-differences the data. The term η_t is a year fixed effect, η_o is a country-fixed effect, and δ_o is a country specific quadratic time trend. The model estimates the causal effect of temperature on productivity under the assumption that year-to-year fluctuations in temperature are as good as randomly assigned, conditional on our time controls.

In this model, the impacts of a change in temperature are assumed to unfold over the L years following the change. A large literature has examined the persistence of the impacts of temperature shocks, and we follow here a recent literature (Nath et al., 2024; Bilal and Känzig, 2024) which assumes that the impacts of temperature on growth rates are persistent, but not permanent.[22] We use $L = 10$ lags to capture persistent effects of temperature shocks on productivity.[23]

Estimating the damage function on the model primitives is similar to the estimation strategy in Cruz and Rossi-Hansberg (2024). However, instead of estimating the parameters

[21] Recovering productivity (Z_{ot}) involves solving a system of nonlinear equations to separate out p_o, which is unobserved, from data on GDP per person. Solving this system requires GDP and population data for every country in the trading network in every year. However, some rows in the WDIs are missing. To interpolate missing GDP data in the WDIs, we fit a regression of log GDP per capita on log population, and add country and year fixed effects, as well as country-specific slopes on time and US GDP per capita. To construct the trade matrix historically, we use our estimated trade costs τ_{od}. We then invert the trade gravity equation to recover a panel of Z_{ot}. We flag observations for which GDP per capita data in any country-year were interpolated and drop those observations from the estimation sample. See Appendix B3.1 for details.

[22] Allowing for the possibility of permanent growth effects of temperature increase, similar to Burke et al., 2015, would increase our damage estimates

[23] Unlike Bilal and Känzig (2024), we only use local temperature as a regressor, and abstract from the effects of global temperature on local productivity, which are absorbed in η_t, as global temperature shocks are difficult to identify from the limited time-series.

of a parametric damage function, we allow for flexible, state-dependent, dynamic marginal effects. As we fit our model such that GDP per capita, $y_{ot} = p_{ot}Z_{ot}$, Equation 2.31 can be thought of as a GDP-per-capita-temperature regression in which we control for spatial spillovers parametrically using the structure of the model, as in Zappala (2024).[24] Appendix Figure B2 compares our estimated productivity damage function to a damage function for raw GDP-PC values, showing that damages estimated on model implied productivity leads to steeper damages.

Figure 2.2 presents the estimated relationship between temperature and productivity from Equation (2.31). Panel A shows the cumulative marginal effect of a one-degree increase in temperature as a function of baseline temperature. For relatively cold countries (such as Russia), where baseline temperatures lie below the estimated optimum of around 11.5C, moderate warming increases productivity. In contrast, countries with hotter baseline climates (such as Nigeria) experience substantial productivity losses as temperatures rise. Panel B decomposes the cumulative marginal effect shown in Panel A for countries with baseline temperatures corresponding to those of Nigeria, the United States, and Russia in 2019. The effects are highly persistent and grow rapidly for hot countries.

Constructing productivity shocks For each GCM (indexed by k), we accumulate the lagged marginal effects for a given path of temperature shocks, updating the climate system as follows,

$$C_{o,t}^{(k)} = C_{o,t-1}^{(k)} + \Delta C_{o,t}^{(k)}, \quad C_{o,0}^{(k)} = C_{o,2019} \ \forall k$$
$$d\ln Z_{o,t}^{(k)} = \sum_{\ell=0}^{H} \left(\hat{\beta}_{0,\ell} + 2\hat{\beta}_{1,\ell} C_{o,t-\ell}^{(k)}\right) \Delta C_{o,t-\ell}^{(k)}.$$

This procedure generates paths of productivity shocks for each country under each climate forecast.

[24] To see this, note that our model implies that prices encode information about trade and migration links across space (see details in Appendix). By analyzing the effect of temperature on Z, rather than y, we are removing the influence of these factors.

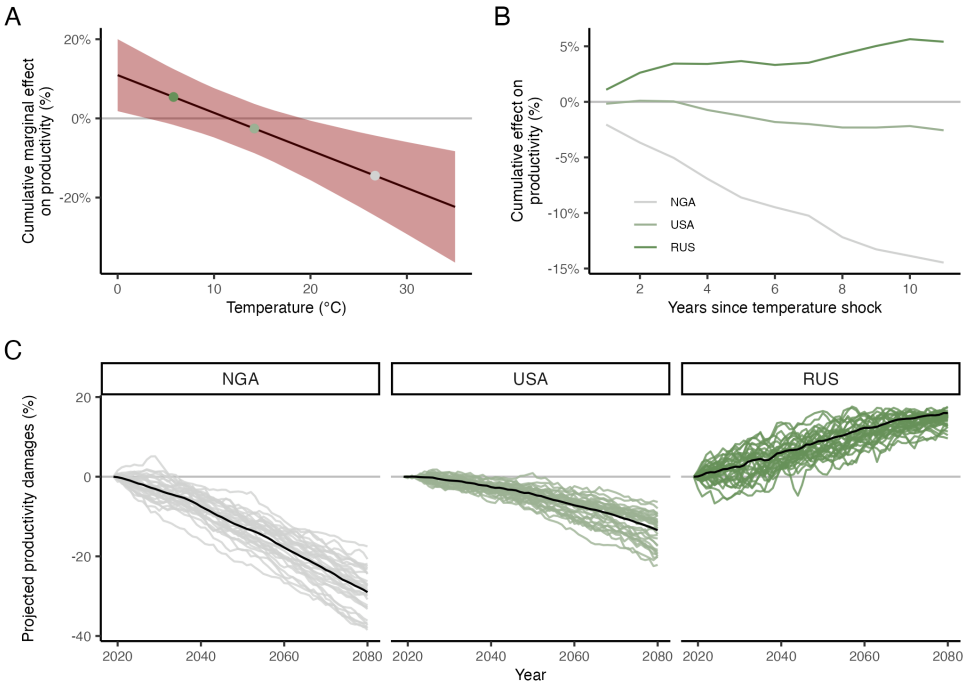


Figure 2.2: **Damage function.**
Panel A presents the estimated relationship between temperature and productivity from Equation (2.31), showing the cumulative marginal effect of a one-degree increase in temperature as a function of annual average temperature. Highlighted points indicate the estimated effects for a cold country (Russia), a temperate country (United States), and a hot country (Nigeria). Panel B reports the cumulative impulse response functions for these countries, illustrating the persistence and timing of productivity responses following a temperature shock. Panel C shows the projected paths of productivity for the same countries, given their projected temperatures across general circulation models (GCMs) in the CMIP6 ensemble. The black lines represent productivity changes associated with the mean projected warming across climate models in each period.

Figure 2.2 shows the estimated productivity shocks implied by the CMIP temperature trajectories for Russia, USA, and Nigeria. Each line represents the evolution of productivity in a given country under a single CMIP6 general circulation model (GCM), based on the estimated temperature–productivity relationship in Equation (2.31). The dispersion across lines reflects uncertainty in future climate outcomes across GCMs, while the black line corresponds to the mean projected productivity path implied by the ensemble-average warming. Consistent with the damage function estimates, hot countries such as Nigeria experience persistent and increasing productivity losses over time, temperate countries such as the United States face moderate declines, and cold countries such as Russia exhibit gains

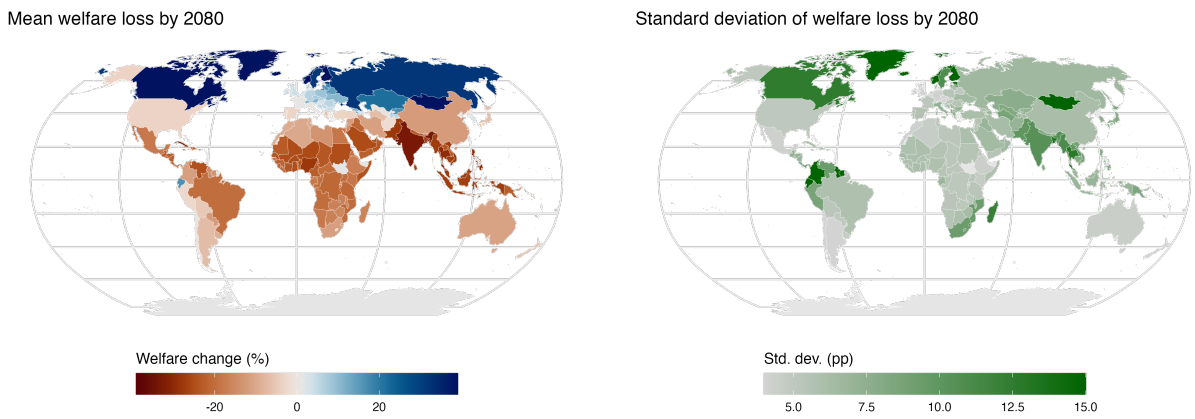


Figure 2.3: Left: welfare changes in 2080 in the mean RCP 8.5 forcing scenario. Right: the standard deviation of welfare outcomes under different CMIP projections in 2080.

under warming.

2.5 Results

2.5.1 The expected welfare impact of climate change

In Figure 2.3, we plot welfare loss by 2080 around the world (left panel). Consistent with a large literature (see, e.g., Cruz and Rossi-Hansberg, 2024), we find welfare gains in northern nations and substantial welfare losses in the global south. Appendix Figure B3 shows the aggregate welfare loss time series. Global welfare loss in 2080 is on average -18.7%, though this ranges from -33.3% to -8.3%. Using global PPP-adjusted GDP in 2019 as a dollar-denominated baseline (140.3 trillion USD), under the roughly 4.6 $GtCO_2$ emitted from 2019-2080 in RCP 8.5, and using a 1% discount rate (as our model abstracts from growth) and assuming damages end in 2080, this leads to a rough social cost of carbon (SCC) estimate of \$90 per tCO_2 – but the range of this SCC estimate across different CMIP projections goes from \$14 to \$192. In Appendix Figure B4, we plot the distribution of SCC estimates under different discount rates. The distribution of SCC estimates is right skew and wider at lower discount rates, as welfare uncertainty is backloaded; we are more uncertain about damages in the future.

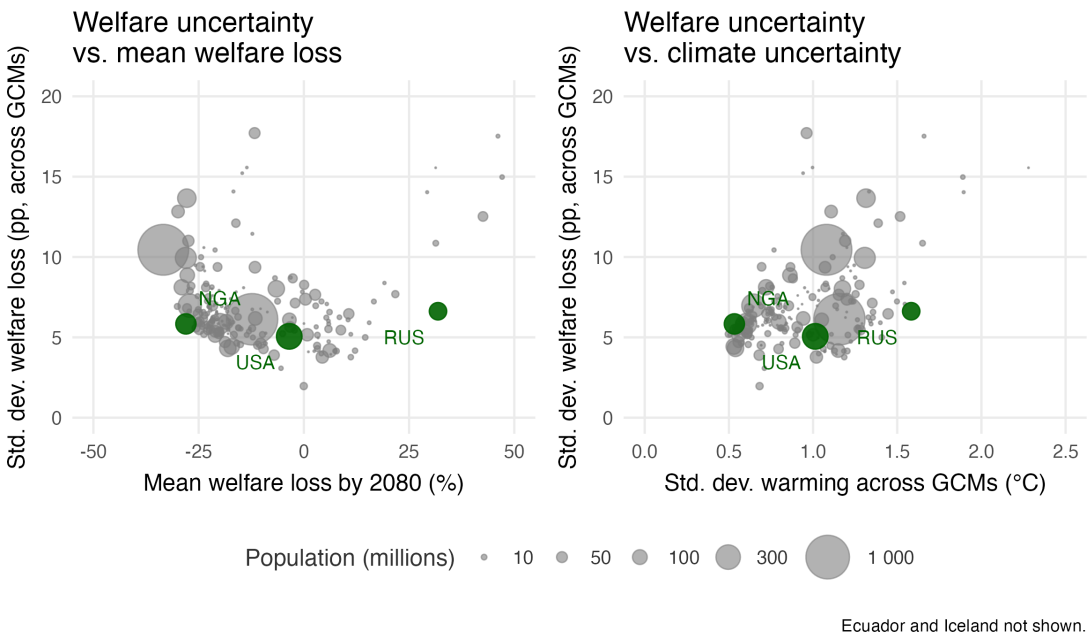


Figure 2.4: Left: Standard deviation of welfare loss by 2080 (in percentage points) against the mean welfare loss by 2080 across countries. Right: the same welfare uncertainty aginst the standard deviation of predicted warming in 2080 across CMIP-6 participating GCMs. Points are sized by their initial population. Ecuador and Iceland are omitted as they are outliers for welfare variance. Nigeria, USA, and Russia are highlighted.

In the right panel, we show the standard deviation of welfare outcomes under different CMIP projections, colored by whether welfare changes are positive or negative at baseline. Welfare variance is higher for Northern Andean and Caribbean Rim nations. These nations are particularly vulnerable to ENSO events, a possible source of forecast uncertainty across CMIP models. We additionally find substantial welfare uncertainty for South and Central Asian countries. This uncertainty may stem from how forecast uncertainty on how climate change affects the Tibetan Plateau – and therefore the Asian Monsoon. Gains in high-latitude nations like Norway, Russia, and Mongolia, are also uncertain. Surprisingly, despite large predicted losses in sub-Saharan Africa, there is little uncertainty in projected welfare losses for most of the sub-continent.

In sum, welfare loss uncertainty is not perfectly explained by the size of the average gains or losses. To make this point clear, in the left panel of Figure 2.4 we show uncertainty in welfare loss against the mean welfare loss. The relationship is somewhat U-shaped, but ab-

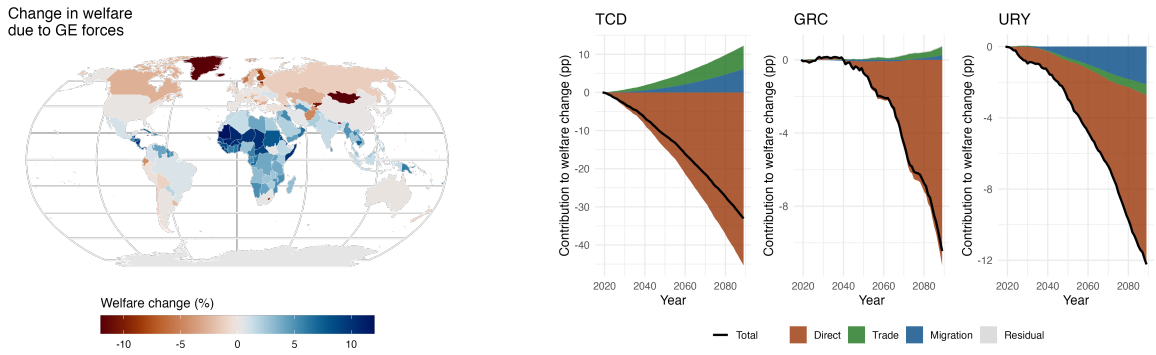


Figure 2.5: Left: the expected welfare impact of climate change in 2080 attributable to general equilibrium forces. Right: a time-series decomposition of these welfare changes for Chad (TCD), Greece (GRC) and Uruguay (URY).

solute welfare change is not totally predictive of welfare loss variance. In the right panel, we plot welfare loss uncertainty against climate uncertainty, as given by the standard deviation of projected warming across CMIP-6 models by 2080. While welfare uncertainty is positively correlated with warming uncertainty, it is not perfectly predictive ($R^2 = 0.25$), which suggests that both the path of warming and nonlinear amplification through the damage function and general equilibrium play important roles in shaping the precision of our welfare loss estimates.

We demonstrate the role trade and migration play in shaping expected welfare change in Figure 2.5. The left panel shows the change in welfare attributable to these general equilibrium forces over space.[25] There is substantial spatial heterogeneity: in sub-Saharan Africa and South and Southeast Asia, trade and migration attenuate the welfare loss from climate change implied by pure damages. Such countries suffer absolute productivity losses, but their terms-of-trade improve, as their relative productivity declines as well: their trading partners (Europe and China) face relatively small productivity changes from climate change. This gain also operates through emigration: as their migration option value rises, these nations depopulate, reducing their output, and subsequently putting upward pressure on

[25] That is, it maps,

$$\mathbb{E}_k \left[\sum_{t=1}^{2080} \left(\boldsymbol{\mathcal{T}}_{t-1} + \boldsymbol{\mathcal{M}}_{t-1} \right) d \ln Z_t^{(k)} + \mathcal{L}_t^{(k)} \right].$$

the price of their exports on international markets.

The right panel of Figure 2.5 shows the role these forces play over time in three select countries. First, in Chad (TCD) and Greece (GRC), direct productivity losses are offset by these trade and migration gains, though in Greece, climate damages occur farther in the future than for Chad. This is because of the nonlinearity of the damage function: local temperature must rise in Greece before the marginal effect of temperature shocks diminish productivity. By contrast, in Uruguay (URY), damages immediately begin to accrue, and general equilibrium forces amplify the welfare cost of climate change. Despite Uruguay suffering from absolute productivity losses rising local temperatures, its regional trading partners (e.g., Brazil) suffer larger climate damages. Consequently, Uruguay's relative productivity improves, diminishing its terms-of-trade. Moreover, Uruguay receives climate migrants from Brazil, further amplifying its welfare losses. Thus, our model demonstrates the extent to which the spatial correlation of climate shocks are filtered through the trade matrix is of first-order importance in projecting the welfare impact of climate change, a point made in Dingel and Meng (2025).

2.5.2 Climate risk over time and space

However, general equilibrium forces matter beyond the first order: they can amplify or attenuate the variance of climate shocks. In Figure 2.6, we plot the % change in the standard deviation of percent changes in welfare by 2080 measured across CMIP-6 models when accounting for trade and migration in addition to productivity shocks. In the left panel, we plot this across space: it is almost everywhere negative. General equilibrium forces dampen welfare variance relative to the variance of productivity shocks implied by the estimated damage function. Moreover, these general equilibrium forces play an important role in reducing welfare risk in sub-Saharan Africa and Central and Southeast Asia, where shock variance is substantial due to intermodel uncertainty in these regions. In the right panel, we plot the contribution to welfare variance (in squared percentage points) from damage function risk,

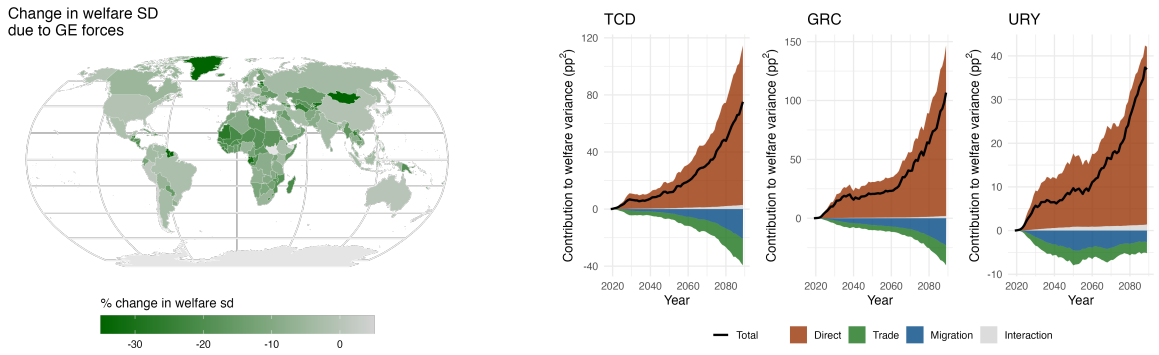


Figure 2.6: Left: The percent change in the variance of welfare changes by 2080 attributable to general equilibrium forces. Right: Decomposing the variance of welfare changes into direct (damage function), trade, and migration, and residual components.

and how this is filtered by the trade and migration matrices. In all three countries, general equilibrium forces play a sizable role in reducing climate risk over time.

In Figure 2.7, we whether the burden of climate risk is borne by the poorest nations today. While the standard deviation of projected warming by 2080 is largest for some of the richest countries today (left panel), this does not translate to lower welfare risk. Rather, we find a modest negative correlation between the level of development and climate risk: a 10% increase in 2019 GDP per capita is associated with a 0.1 fall in the standard deviation of projected warming by 2080.[26]

However, we do find that trade and adaptation matter most for some of the poorest regions in the world. In the left panel of Figure 2.8, we plot the percent change in the standard deviation of welfare changes by 2080 against baseline log GDP per capita. We find that the reduction in climate risk due to trade and migration is larger for poorer countries: a 1 log point decrease in log GDP per capita is associated with a 2 percentage point reduction in climate risk due to general equilibrium forces (Appendix Table B2). Absent adaptation, international inequality in climate risk, as measured by the Gini coefficient of the variance of log changes in welfare by 2080 is about 40% as large as international income inequality (as measured by the Gini coefficient for GDP per capita). Accounting for trade and migration reduces climate risk inequality by about 7 percentage points.

[26]This correlation is population-weighted; T-statistic> 7, $R^2 = 0.22$.

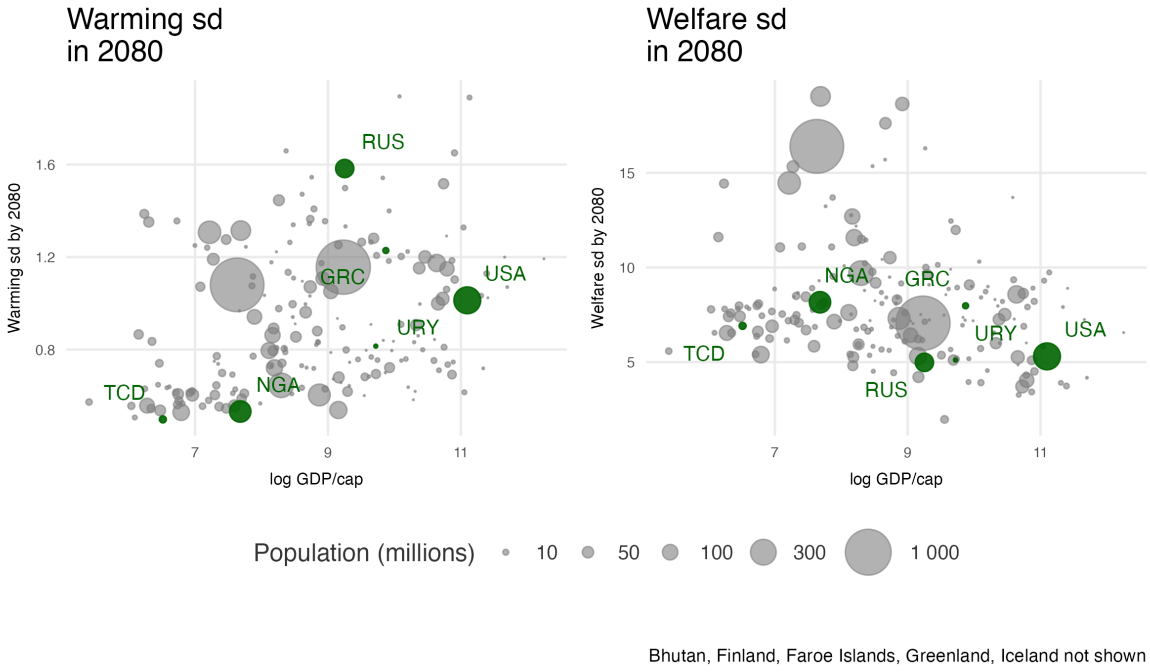


Figure 2.7: Left: standard deviation of degrees C of warming by 2080 across CMIP-6 models vs. log GDP/cap in 2019. Right: standard deviation of % changes in welfare by 2080 under different CMIP-6 model temperature forecasts vs. log GDP/cap. Small nations with large intermodel variation in projected warming like Iceland are omitted.

However, the level of development is not the only predictor of the capacity for trade and migration to lower climate risk. We additionally find that a country's trade openness at baseline matters in shaping the ability for economic geography forces to attenuate climate risk.[27] In the right panel of Figure 2.8, we show that it is in open economies that the reduction in climate risk due to trade and migration is largest. These countries have the largest capacity at baseline to diversify their exposure to climate risk. We find that a 1 log point change in trade openness is associated with a 5 percentage point reduction in climate risk due to trade and migration (see Appendix Table B2).

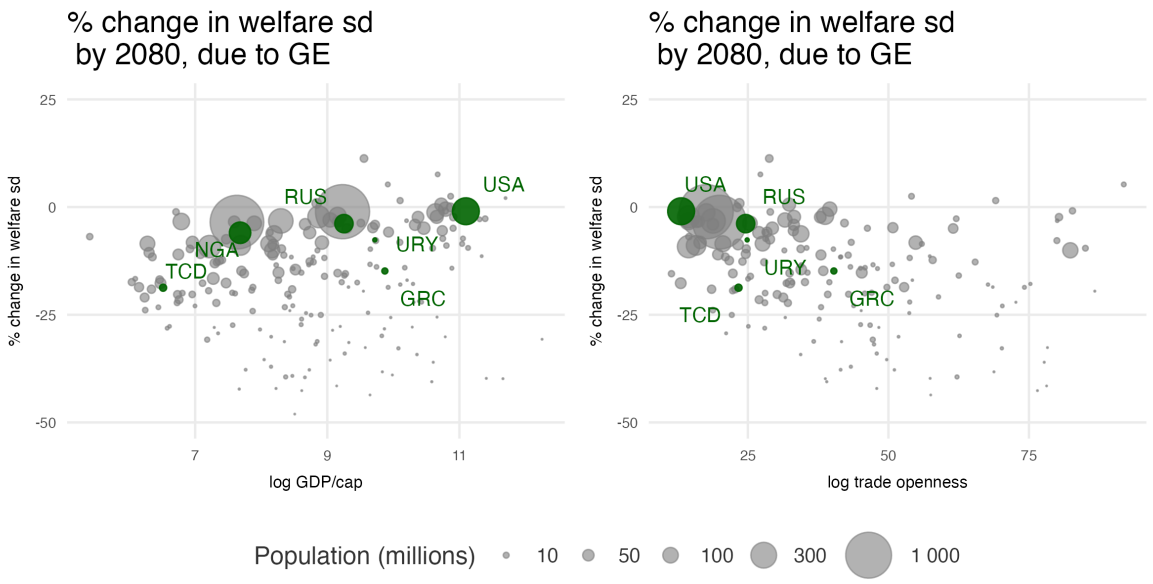


Figure 2.8: Left: the % change in the standard deviation of % changes in welfare by 2080 attributable to GE forces like trade and migration vs. log GDP/cap in 2019. Right: 2019 log GDP on the x-axis. In the left panel, Bhutan, Finland, Faroe Islands, Greenland, Iceland are not shown. In the right panel, Djibouti, Hong Kong, Ireland, Luxembourg, Malta, San Marino, and Singapore are not shown.

2.5.3 Jensen's correction

As the model is highly nonlinear, both due to the nonlinearity of the quadratic damage function with persistent effects and the structure of the model's equilibrium, it is plausible that expected welfare changes when integrating over future climate scenarios differ from the welfare changes computed using the mean temperature forecast across models due to Jensen's inequality.

In the left panel of Figure 2.9, we plot the percentage point change adjustment to welfare changes by 2080 that comes from integrating over CMIP-6 models, instead of filtering the ensemble mean through the model, that is, we plot the Jensen's correction JC,

$$JC_{2080} = \mathbb{E}_k \left[\ln \mathcal{W}_{2080}^{(k)} \right] - \overline{\ln \mathcal{W}_{2080}}$$

[27] We measure trade openness as $\frac{1}{2} \frac{\text{Imports+Exports}}{\text{GDP}}$ in 2019. We take this from the World Development Indicators' NE.TRD.GNFS.ZS series.

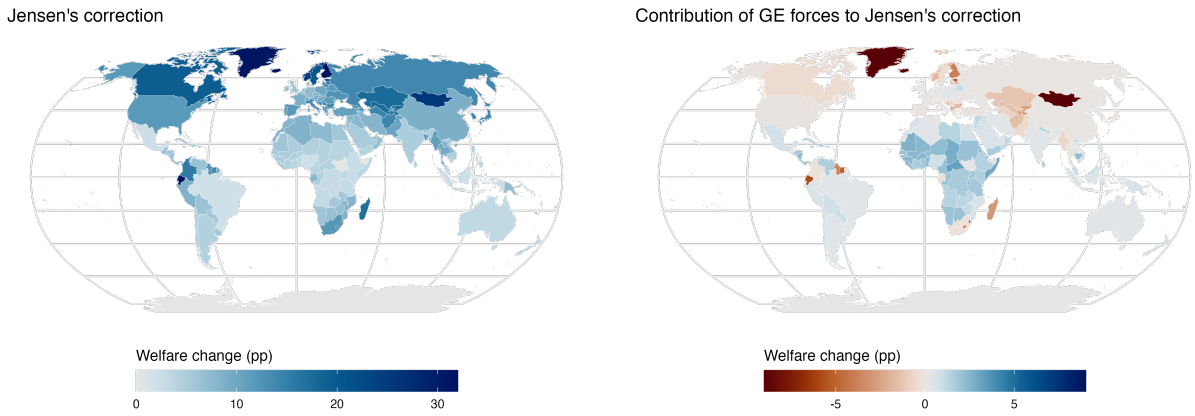


Figure 2.9: Left: percentage point welfare change adjustment when accounting for Jensen's inequality. Right: the percentage point change in Jensen's correction attributable to trade and migration.

where $\overline{\ln \mathcal{W}_{2080}}$ is the projected change in welfare evaluated at the mean CMIP-6 model temperature forecast. Using our linear decomposition, we are able to separate out the component of Jensen's correction attributable to the nonlinearity of the damage function from the nonlinearities from adaptation in the model, that is,

$$JC_{2080} = \underbrace{\mathbb{E}_k\left[\sum_{t=0}^{2080} d\ln Z_t^{(k)}\right] - \sum_{t=0}^{2080}\overline{d\ln Z_t}}_{\text{damage function nonlinearity}} + \underbrace{\mathbb{E}_k\left[\sum_{t=0}^{2080}\left(\boldsymbol{\mathcal{T}}_{t-1}^{(k)} + \boldsymbol{\mathcal{M}}_{t-1}^{(k)}\right) d\ln Z_t^{(k)}\right] - \sum_{t=0}^{2080}\left(\overline{\boldsymbol{\mathcal{T}}}_{t-1} + \overline{\boldsymbol{\mathcal{M}}}_{t-1}\right)\overline{d\ln Z_t}}_{\text{general equilibrium adaptation nonlinearities}}.$$

The term $\mathbb{E}_k\left[d\ln Z_t^{(k)}\right] \neq \overline{d\ln Z_t}$ because $d\ln Z_t$ is a nonlinear function of the climate state $\{C_t^{(k)}\}_t$. In the right panel of Figure 2.9, we plot the component of Jensen's correction attributable to general equilibrium adaptation forces around the world. These are largest in sub-Saharan Africa, where adaptation forces play an important role in shaping the concavity of the welfare function and attenuating expected welfare losses when integrating over the distribution of future climate shocks.[28]

[28] In Appendix Figure B5 we plot this decomposition over time for six countries.

2.6 Conclusion

This paper develops a framework to understand how climate risk propagates through the global economy and how both a nonlinear, dynamic damage function, coupled with general-equilibrium forces—trade and migration—reshape both the expected cost and the variance of welfare under climate change. Motivated by the observation that climate projections remain deeply uncertain and that damages are highly nonlinear, we focus on how spatial linkages mediate not only the mean impact of warming but also the risk surrounding it. While prior research has shown that trade and migration can reallocate activity in response to climate change, we demonstrate that these same forces play a crucial role in redistributing and, in many cases, reducing welfare risk across space.

We estimate a nonlinear, dynamic damage function that maps changes in temperature to model-implied productivity. Using a long annual panel of country-level data, we exploit within-country temperature variation to identify both the immediate and persistent impacts of warming on productivity. Our flexible distributed-lag specification allows for delayed responses, capturing persistent effects or local adaptation adjust productivity over the subsequent decade. This empirical foundation generates a rich and robust mapping from temperature to productivity that we embed directly into our quantified model, enabling stochastic simulations grounded in observed economic responses.

We then build and quantify a tractable dynamic spatial model that connects countries through trade and migration. These channels serve as margins of adaptation, allowing agents to reallocate resources in response to climate shocks, and as mechanisms of propagation, transmitting those shocks across borders and over time. The model incorporates risk in both the magnitude and geography of future warming by introducing stochastic fundamentals that evolve according to the estimated damage process. Within this environment, we derive analytical first- and second-order welfare approximations that decompose welfare changes into direct, trade, and migration components. The first-order terms describe how mean

welfare responds to expected changes in productivity, while the second-order terms capture the curvature in welfare induced by nonlinear damages and general equilibrium feedback. Together, these decompositions provide a clear and tractable way to quantify how adaptation and exposure jointly shape the geography of climate risk.

Applying this framework globally, we decompose welfare outcomes into direct and general-equilibrium components for every country in the world. Consistent with past work, we find that welfare loss from climate change is most severe in poor, hot countries, while some rich, cold nations experience gains. Our first-order welfare decomposition shows that in much of sub-Saharan Africa and South and Southeast Asia, trade and migration attenuate direct welfare losses by facilitating reallocation toward less-affected regions. In other parts of the world, however, these forces can amplify damages through adverse terms-of-trade effects (when productivity falls relative to key trading partners) or migration flows that shift exposure across borders.

Examining climate risk, our results reveal a striking degree of spatial heterogeneity. Spatial climate risk inequality is almost half as large as global income inequality, with the burden falling on low income nations. Trade and migration substantially dampen welfare volatility almost everywhere, though to very different degrees. Highly integrated, low-income economies experience the greatest reductions in welfare variance due to trade and migration—up to 25–40 percent reductions in climate risk—compared to insular, higher-income nations like United States or Russia, who see minimal reductions in climate risk through these channels.

These patterns have direct policy implications. The benefits of global integration extend beyond traditional gains from trade and migration—they also provide a form of insurance against climate risk. More open economies are able to diversify exposure through international linkages, whereas closed economies remain more vulnerable to domestic climate variability. The geography of integration thus determines not only the expected cost of climate change but also the stability of welfare outcomes. Policies that facilitate smoother

trade and migration flows, or that promote diversified regional production networks, can therefore mitigate both the mean and variance of global welfare losses.

Beyond the specific application to climate change, the framework developed in this paper can be used more broadly to study a wide range of shocks in quantitative spatial models. The theory provides a clean and general decomposition of welfare changes into direct, trade, and migration components, which together map productivity shocks into welfare outcomes through clearly interpretable mechanisms. This structure allows researchers to analyze how different types of shocks—such as technological innovation, policy interventions, geopolitical disruptions, or supply-chain disturbances—propagate across space and shape welfare both on average and its variance. In this sense, our model offers a flexible tool for studying how the geography of global integration mediates the welfare consequences of any stochastic disturbance that affects regional productivity.

Ultimately, this paper shows that exposure to climate risk is shaped as much by economic geography as by the climate system itself. Global linkages reduce the welfare risk for countries around the world, some more than others. The broader implication is that managing climate risk requires not only reducing emissions, but also building the institutional and economic linkages that allow regions to adapt collectively in an uncertain world.

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Appendix A: Technology and the Geography of Industrial Policy

A1 Quantitative Model

A1.1 Household optimization

Households have demand across regions and sectors paramaterized by a nested CES:

$$c_i = \left(\sum_k \kappa_k^{1/\sigma} (c_{ik})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \qquad c_{ik} = \left(\sum_{j \in N} c_{i,jk}^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}}.$$

Workers in each region then solve the following optimization problem to determine optimal consumption spending:

$$\mathcal{L} = \left(\sum_k \kappa_k^{1/\sigma} \left(\sum_j c_{j,ik}^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi(\sigma-1)}{\sigma(\psi-1)}} \right)^{\frac{\sigma}{\sigma-1}} + \lambda_i \left(w_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} \right),$$

the first-order condition for which is:

$$\begin{aligned} \{c_{i,jk}\} : & \frac{\sigma}{\sigma-1} \kappa_k^{1/\sigma} c_i^{1/\sigma} \frac{\psi(\sigma-1)}{(\psi-1)\sigma} c_{ik}^{\frac{\sigma-\psi}{\sigma\psi}} \frac{\psi-1}{\psi} c_{i,jk}^{-1/\psi} = \lambda_i p_{jk} \tau_{ji} \\ & \frac{1}{\lambda_i} \kappa_k^{\frac{1}{\sigma}} c_i^{\frac{1}{\sigma}} c_{ik}^{\frac{\sigma-\psi}{\sigma\psi}} c_{i,jk}^{-1/\psi} = p_{jk} \tau_{ji}, \end{aligned} \tag{A.32}$$

which yields the following demand:

$$p_{i,jk}c_{i,jk} = \kappa_k \frac{p_{i,jk}^{1-\psi} P_{ik}^{\psi-\sigma}}{P_i^{1-\sigma}} w_i, \tag{A.33}$$

where

$$\begin{aligned}
p_{i,jk} &= \tau_{ji} p_{jk} \\
P_{ik} &= \left(\sum_j p_{i,jk}^{1-\psi} \right)^{\frac{1}{1-\psi}} \\
P_i &= \left(\sum_k \kappa_k P_{ik}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.
\end{aligned}$$

We check that the spending across all goods equals income:

$$\begin{aligned}
\sum_j \sum_k p_{i,jk}c_{i,jk} &= \frac{w_i}{P_i^{1-\sigma}} \sum_k \kappa_k P_{ik}^{\psi-\sigma} \sum_j p_{i,jk}^{1-\psi} \\
&= \frac{w_i}{P_i^{1-\sigma}} \sum_k \kappa_k P_{ik}^{\psi-\sigma} P_{ik}^{1-\psi} \\
&= \frac{w_i}{P_i^{1-\sigma}} \sum_k \kappa_k P_{ik}^{1-\sigma} \\
&= \frac{w_i}{P_i^{1-\sigma}} P_i^{1-\sigma} = w_i.
\end{aligned}$$

A1.2 Firm level optimization

Firms have a CES production function $q_{ik} = z_{ik}^{\iota} \left(\alpha_k^{1/\gamma} (z_{ik}^{1-\iota} L_{ik})^{\frac{\gamma-1}{\gamma}} + (1-\alpha_k)^{1/\gamma} H_{ik}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}$, for which the firm solves the following cost-minimization problem:

$$\mathcal{L} = \min_{L_{ik}, H_{ik}} \; w_i L_{ik} + r_i H_{ik} + \lambda \left(q_{ik} - z_{ik}^{\iota} \left(\alpha_k^{1/\gamma} (z_{ik}^{1-\iota} L_{ik})^{\frac{\gamma-1}{\gamma}} + (1-\alpha_k)^{1/\gamma} H_{ik}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}} \right).$$

First order conditions yield:

$$\{L_{ik}\} : w_i = \lambda z_i^{\iota} \alpha_k^{1/\gamma} \left(\alpha_k^{1/\gamma} (z_{ik}^{1-\iota} L_{ik})^{\frac{\gamma-1}{\gamma}} + (1-\alpha_k)^{1/\gamma} H_{ik}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{1}{\gamma-1}} z_{ik}^{\frac{(1-\iota)(\gamma-1)}{\gamma}} L_{ik}^{-1/\gamma}$$

$$\{H_{ik}\} : r_i = \lambda z_i^{\iota} (1-\alpha_k)^{1/\gamma} \left(\alpha_k^{1/\gamma} (z_{ik}^{1-\iota} L_{ik})^{\frac{\gamma-1}{\gamma}} + (1-\alpha_k)^{1/\gamma} H_{ik}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{1}{\gamma-1}} H_{ik}^{-1/\gamma}.$$

The optimal ratio between inputs is:

$$\begin{aligned} \frac{w_i}{r_i} &= \left(\frac{\alpha_k}{1-\alpha_k} \right)^{1/\gamma} \frac{z_{ik}^{\frac{(1-\iota)(\gamma-1)}{\gamma}} L_{ik}^{-1/\gamma}}{H_{ik}^{-1/\gamma}} \\ \rightarrow \frac{L_{ik}}{H_{ik}} &= \frac{\alpha_k}{1-\alpha_k} z_{ik}^{(1-\iota)(\gamma-1)} \left(\frac{r_i}{w_i} \right)^{\gamma}. \end{aligned} \tag{A.34}$$

Plugging (A.34) into output q_{ik}:

$$
\begin{aligned}
q_{ik} &= z_{ik}^{\iota}\left(\alpha_k^{1/\gamma}(z_{ik}^{1-\iota}L_{ik})^{\frac{\gamma-1}{\gamma}} + (1-\alpha_k)^{1/\gamma}\left(\frac{1-\alpha_k}{\alpha_k}z_{ik}^{-(1-\iota)(\gamma-1)}\left(\frac{w_i}{r_i}\right)^{\gamma}L_{ik}\right)^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}^{\iota}L_{ik}\left(\alpha_k^{1/\gamma}z_{ik}^{(1-\iota)\frac{\gamma-1}{\gamma}} + (1-\alpha_k)\alpha_k^{\frac{1-\gamma}{\gamma}}z_{ik}^{-(1-\iota)\frac{(\gamma-1)^2}{\gamma}}\frac{r_i^{1-\gamma}}{r_i^{1-\gamma}}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}^{\iota}L_{ik}\left(\frac{\alpha_k^{1/\gamma}z_{ik}^{(1-\iota)\frac{\gamma-1}{\gamma}}w_i^{1-\gamma} + (1-\alpha_k)\alpha_k^{\frac{1-\gamma}{\gamma}}z_{ik}^{-(1-\iota)\frac{(\gamma-1)^2}{\gamma}}r_i^{1-\gamma}}{w_i^{1-\gamma}}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}^{\iota}L_{ik}\left(\frac{\alpha_k^{1/\gamma}z_{ik}^{(1-\iota)\frac{\gamma-1}{\gamma}}w_i^{1-\gamma} + \alpha_k^{1/\gamma}z_{ik}^{(1-\iota)\frac{\gamma-1}{\gamma}}(1-\alpha_k)\alpha_k^{-1}z_{ik}^{-(1-\iota)(\gamma-1)}r_i^{1-\gamma}}{w_i^{1-\gamma}}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}^{\iota}L_{ik}\alpha_k^{1/(\gamma-1)}z_{ik}^{\iota-1}w_i^{\gamma}\left(w_i^{1-\gamma} + \frac{(1-\alpha_k)r_i^{1-\gamma}}{\alpha_k z_{ik}^{(1-\iota)(\gamma-1)}}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}L_{ik}\alpha_k^{1/(\gamma-1)}w_i^{\gamma}\left(\frac{\alpha_k z_{ik}^{(1-\iota)(\gamma-1)}w_i^{1-\gamma} + (1-\alpha_k)r_i^{1-\gamma}}{\alpha_k z_{ik}^{(1-\iota)(\gamma-1)}}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}L_{ik}\alpha_k^{1/(\gamma-1)}\alpha_k^{-\gamma/(\gamma-1)}w_i^{\gamma}z_{ik}^{-(1-\iota)\gamma}\left(\alpha_k\left(\frac{w_i}{z_{ik}^{1-\iota}}\right)^{1-\gamma} + (1-\alpha_k)r_i^{1-\gamma}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}L_{ik}\alpha_k^{-1}w_i^{\gamma}z_{ik}^{-(1-\iota)\gamma}\left(\alpha_k\left(\frac{w_i}{z_{ik}^{1-\iota}}\right)^{1-\gamma} + (1-\alpha_k)r_i^{1-\gamma}\right)^{\frac{\gamma}{\gamma-1}} \\
q_{ik} &= z_{ik}^{\iota}L_{ik}\alpha_k^{-1}w_i^{\gamma}z_{ik}^{-(1-\iota)(\gamma-1)}\left(\alpha_k\left(\frac{w_i}{z_{ik}^{1-\iota}}\right)^{1-\gamma} + (1-\alpha_k)r_i^{1-\gamma}\right)^{\frac{\gamma}{\gamma-1}},
\end{aligned}
$$

which lets us solve for labor demand:

$$
L_{ik}^{*} = \alpha_k q_{ik} z_{ik}^{-\iota}w_i^{-\gamma}z_{ik}^{(1-\iota)(\gamma-1)}\left(\alpha_k\left(\frac{w_i}{z_{ik}^{1-\iota}}\right)^{1-\gamma} + (1-\alpha_k)r_i^{1-\gamma}\right)^{\frac{\gamma}{1-\gamma}}. \tag{A.35}
$$

Plugging in and solving for H_{ik}:

$$
\begin{aligned}
H_{ik}^{*} &= \frac{1-\alpha_k}{\alpha_k}\left(\frac{w_i}{r_i}\right)^{\gamma}z_{ik}^{-(1-\iota)(\gamma-1)}L_{ik}^{*} \\
&= (1-\alpha_k)q_{ik}z_{ik}^{-i}r_i^{-\gamma}\left(\alpha_k\left(\frac{w_i}{z_{ik}^{1-\iota}}\right)^{1-\gamma} + (1-\alpha_k)r_i^{1-\gamma}\right)^{\frac{\gamma}{1-\gamma}}.
\end{aligned} \tag{A.36}
$$

Plugging these into the cost function:

$$c_{ik}^{*} = \frac{q_{ik}}{z_{ik}^{\iota}} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{1}{1-\gamma}}.$$

As such, we can now obtain the marginal cost and price:

$$mc_{ik} = p_{ik} = z_{ik}^{-\iota} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{1}{1-\gamma}}. \tag{A.37}$$

A1.3 Aggregate equilibrium

For given: $\{\bar{a}_i, \bar{z}_{ik}, \bar{L}, \bar{H}_i, \tau_{ij}, , \alpha_k, \nu, \theta, \phi_k, \sigma, \psi, \gamma, \kappa_k, \iota\}$:

The equilibrium is given by values for prices $\{p_{i,jk}, p_{ik}, P_j, P_{jk}, w_i, r_i\}$, local income I_i, con-

gestion and spillovers $\{a_i, z_{ik}\}$, and quantities $\{L_{ik}, H_{ik}, L_i, q_{ik}, C_{i,jk}\}$ such that:

$$p_{i,jk}C_{i,jk} = \alpha_k \frac{p_{i,jk}^{1-\psi} P_{ik}^{\psi-\sigma}}{P_i^{1-\sigma}} I_i \qquad (N^2K \text{ eqs.}) \quad \text{(A.38)}$$

$$P_{ik} = \left(\sum_j p_{i,jk}^{1-\psi} \right)^{\frac{1}{1-\psi}} \qquad (NK \text{ eqs.}) \quad \text{(A.39)}$$

$$P_i = \left(\sum_j \kappa_k P_{ik}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \qquad (N \text{ eqs.}) \quad \text{(A.40)}$$

$$I_i = w_i L_i + r_i H_i \qquad (N \text{ eqs.}) \quad \text{(A.41)}$$

$$q_{jk} = \sum_j \tau_{ij} C_{j,ik} \qquad (NK \text{ eqs.}) \quad \text{(A.42)}$$

$$a_i = \bar{a}_i L_i^{-\theta} \qquad (N \text{ eqs.}) \quad \text{(A.43)}$$

$$z_{ik} = \bar{z}_{ik} L_{ik}^{\phi_k} \qquad (NK \text{ eqs.}) \quad \text{(A.44)}$$

$$L_i = \frac{(\frac{a_i w_i}{P_i})^{\nu}}{\sum_{j=1}^{N} (\frac{a_j w_j}{P_j})^{\nu}} \bar{L} \qquad (N \text{ eqs.}) \quad \text{(A.45)}$$

$$L_{ik} = \alpha_k z_{ik}^{-\iota} w_i^{-\gamma} z_{ik}^{(1-\iota)(\gamma-1)} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}} q_{ik} \qquad (NK \text{ eqs.}) \quad \text{(A.46)}$$

$$H_{ik} = (1-\alpha_k) z_{ik}^{-\iota} r_i^{-\gamma} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}} q_{ik} \qquad (NK \text{ eqs.}) \quad \text{(A.47)}$$

$$p_{ik} = z_{ik}^{-\iota} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \qquad (NK \text{ eqs.}) \quad \text{(A.48)}$$

$$p_{i,jk} = \tau_{ij} p_{ik} \qquad (N^2K \text{ eqs.}) \quad \text{(A.49)}$$

$$\sum_k L_{ik} = L_i \qquad (N \text{ eqs.}) \quad \text{(A.50)}$$

$$\sum_k H_{ik} = \bar{H}_i \qquad (N \text{ eqs.}) \quad \text{(A.51)}$$

As such, we have $2N^2K + 6NK + 6N$ equations in $2N^2K + 6NK + 6N$ unknowns.

A2 Inversion

The goal of the inversion is to rationalize observed w_i, r_i, L_{ik}, L_i as an equilibrium of the model given the model parameters. The inversion is done in a two-step process. First, we recover productivity to rationalize the observed wages and population, then given those productivites, we construct price indices and invert the population equation to recover amenities.

A2.1 Productivities

I use a combination of goods market clearing and firms' labor optimality:

$$L_{ik} w_i^{\gamma} = \alpha_k q_{ik} z_{ik}^{-\iota} z_{ik}^{(1-\iota)(\gamma-1)} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}},$$

where $q_{ik} = \kappa_k p_{ik}^{-\psi} \sum_j \frac{\tau_{ij}^{-\psi} P_{jk}^{\psi-\sigma}}{P_j^{1-\sigma}} y_j$

$$
\begin{aligned}
& L_{ik} w_i^{\gamma} = \alpha_k z_{ik}^{-\iota} z_{ik}^{(1-\iota)(\gamma-1)} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}} \kappa_k p_{ik}^{-\psi} \sum_j \frac{\tau_{ij}^{-\psi} P_{jk}^{\psi-\sigma}}{P_j^{1-\sigma}} y_j \\
\rightarrow\ & L_{ik} w_i^{\gamma} = \alpha_k \kappa_k z_{ik}^{-\iota} z_{ik}^{(1-\iota)(\gamma-1)} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}} \\
& z_{ik}^{\iota\psi} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{-\psi}{1-\gamma}} \sum_j \frac{\tau_{ij}^{-\psi} P_{jk}^{\psi-\sigma}}{P_j^{1-\sigma}} y_j \\
\rightarrow\ & L_{ik} w_i^{\gamma} = \alpha_k \kappa_k z_{ik}^{\iota(\psi-1)} z_{ik}^{(1-\iota)(\gamma-1)} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma-\psi}{1-\gamma}} \sum_j \frac{\tau_{ij}^{-\psi} P_{jk}^{\psi-\sigma}}{P_j^{1-\sigma}} y_j \\
\rightarrow\ & L_{ik} w_i^{\gamma} = \alpha_k \kappa_k z_{ik}^{\iota(\psi-1)+(1-\iota)(\gamma-1)} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma-\psi}{1-\gamma}} \sum_j \frac{\tau_{ij}^{-\psi} P_{jk}^{\psi-\sigma}}{P_j^{1-\sigma}} y_j \\
\rightarrow\ & z_{ik}^{\iota(1-\psi)+(1-\iota)(1-\gamma)} = \alpha_k \kappa_k w_i^{-\gamma} L_{ik}^{-1} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma-\psi}{1-\gamma}} \sum_j \frac{\tau_{ij}^{-\psi} P_{jk}^{\psi-\sigma}}{P_j^{1-\sigma}} y_j \\
\rightarrow\ & z_{ik} = \left(\alpha_k \kappa_k w_i^{-\gamma} L_{ik}^{-1} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{\gamma-\psi}{1-\gamma}} \sum_j \frac{\tau_{ij}^{-\psi} P_{jk}^{\psi-\sigma}}{P_j^{1-\sigma}} y_j \right)^{\frac{1}{\iota(1-\psi)+(1-\iota)(1-\gamma)}},
\end{aligned}
$$

where the price indices for each region and region-sector further depend on productivities everywhere:

$$
\begin{aligned}
P_{jk} &= \left(\sum_i \left(z_{ik}^{-\iota} \left(\alpha_k \left(\frac{w_i}{z_{ik}^{1-\iota}} \right)^{1-\gamma} + (1-\alpha_k) r_i^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right)^{1-\psi} \right)^{\frac{1}{1-\psi}} \\
P_j &= \left(\sum_k \kappa_k P_{jk}^{1-\sigma} \right)^{1-\sigma}. \qquad \text{(A.52)}
\end{aligned}
$$

A2.2 Amenities

We can use productivities obtained in the previous section to get a price index for each region as highlighted in (A.52). We can then obtain amenities up to an arbitrary scale:

$$
\begin{aligned}
L_i &= \frac{(\frac{a_i w_i}{P_i})^\nu}{\sum_j (\frac{a_j w_j}{P_j})^\nu} L \\
a_i &= \left(\frac{L_i}{L}\right)^{1/\nu} \frac{P_i}{w_i} \left(\sum_j (\frac{a_j w_j}{P_j})^\nu\right)^{1/\nu} \\
\bar{a}_i L_i^{-\theta} &= L_i^{1/\nu} \frac{P_i}{w_i} \Gamma \\
\rightarrow \bar{a}_i &\propto L_i^{\frac{1}{\nu}+\theta} \frac{P_i}{w_i}.
\end{aligned}
$$

A3 The social planner problem

This section describes the planner's problem taking as given that workers can freely choose where to live, and are ex-ante homogeneous. Under this assumption, the planner maximizes the expected utility of a worker:

$$
W = \Gamma(\frac{\nu-1}{\nu}) \left(\sum_{i=1}^{N} (a_i c_i)^\nu\right)^{1/\nu}, \tag{A.53}
$$

where recall that c_i is a nested CES aggregator of goods across different region-sectors:

$$
c_i = \left(\sum_k \kappa_k^{1/\sigma} (c_{ik})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{A.54}
$$

$$
c_{ik} = \left(\sum_{j \in N} c_{i,jk}^{\frac{\psi-1}{\psi}}\right)^{\frac{\psi}{\psi-1}}. \tag{A.55}
$$

The planner then maximizes (A.53) subject to the resource constraints for final goods

$$
\sum_j \tau_{ij} C_{j,ik} = z_{ik}^{\iota} f_k \left(z_{ik}^{1-\iota} L_{ik}, H_{ik}\right) \qquad \forall i \in N, k \in K, \tag{A.56}
$$

labor market constraints in all regions,

$$\sum_k L_{ik} = L_i \qquad \forall i \in N, \tag{A.57}$$

where labor supply in each region is given

$$\frac{(a_i c_i)^\nu}{\sum_j (a_j c_j)^\nu} \bar{L} = L_i \qquad \forall i \in N, \tag{A.58}$$

the land market clearing constraint in all regions

$$\sum_k H_{ik} = \bar{H}_i \qquad \forall i \in N \tag{A.59}$$

From the labor market constraints across sectors within each region (A.57) and labor supply in each region (A.58), it follows that the national labor market clears

$$\sum_i L_i = \bar{L} \tag{A.60}$$

We can set up the lagrangian:

$$\begin{aligned}
\mathcal{L} = \max_{\{L_i, L_{ik}, H_{ik}, c_i, c_{i,jk}, c^l_{i,jk}\}} & \Gamma\left(\frac{\nu-1}{\nu}\right)\left(\sum_{i=1}^{N}(a_i c_i)^\nu\right)^{1/\nu} \\
& + \sum_i \eta_i \left[c_i - \left(\sum_k \kappa_k^{1/\sigma} \left(\sum_j c_{j,ik}^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi(\sigma-1)}{\sigma(\psi-1)}} \right)^{\frac{\sigma}{\sigma-1}} \right] \\
& + \sum_i \mu_i \left[L_i - \frac{(a_i c_i)^\nu}{\sum_j (a_j c_j)^\nu} \bar{L} \right] + \sum_i \tilde{w}_i \left[L_i - \sum_k L_{ik} \right] + \sum_i \tilde{r}_i \left[\bar{H}_i - \sum_k H_{ik} \right] \\
& + \sum_i \sum_k \tilde{p}_{ik} \left[z_{ik}^\iota f_k(z_{ik}^{1-\iota} L_{ik}, H_{ik}) - \sum_j \tau_{ij} C_{j,ik} \right]
\end{aligned} \tag{A.61}$$

Note that allowing for migration costs adds some complexity into this problem. Workers are ex-ante not identical, since they all have a starting location which has varying access to other

regions conditional on that region's migration costs to other regions. We need to account for this in the expected welfare condition as well as the regional populations in equilibrium:

$$\begin{aligned}\mathcal{L} = \max_{\{L_i, L_{ik}, H_{ik}, c_i, c_{i,jk}, c^l_{i,jk}\}} & \Gamma(\frac{\nu-1}{\nu}) \sum_{i=1}^{N} \alpha_i L_i^0 \left(\sum_j (\frac{a_j c_j}{\mu_{ij}})^\nu \right)^{1/\nu} \\ & + \sum_i \eta_i \left[c_i - \left(\sum_k \kappa_k^{1/\sigma} \left(\sum_j c_{j,ik}^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi(\sigma-1)}{\sigma(\psi-1)}} \right)^{\frac{\sigma}{\sigma-1}} \right] \\ & + \sum_i \chi_i \left[L_i - \sum_{j=1}^{N} \frac{(\frac{a_i c_i}{\mu_{ji}})^\nu}{\sum_{n=1}^{N} (\frac{a_n c_n}{\mu_{jn}})^\nu} L_j^0 \right] + \sum_i \tilde{w}_i \left[L_i - \sum_k L_{ik} \right] + \\ & + \sum_i \tilde{r}_i \left[\bar{H}_i - \sum_k H_{ik} \right] + \sum_i \sum_k \tilde{p}_{ik} \left[z_{ik}^\iota f_k(z_{ik}^{1-\iota} L_{ik}, H_{ik}) - \sum_j \tau_{ij} C_{j,ik} \right]\end{aligned} \tag{A.62}$$

A4 Solving the planner problem

This section solves the planner's problem for interior allocations, i.e, for cases when $L_{ik} > 0 \; \forall i, k$, $H_{ik} > 0 \; \forall i, k$ and $c_{i,jk} > 0 \; \forall i, j, k$. I obtain the following first order conditions solving the lagrangian:

$$\begin{aligned}\{c_{i,jk}\} : & -\eta_i \frac{\sigma}{\sigma-1} \kappa_k^{1/\sigma} c_i^{1/\sigma} \frac{\psi(\sigma-1)}{(\psi-1)\sigma} c_{ik}^{\frac{\sigma-\psi}{\sigma\psi}} \frac{\psi-1}{\psi} c_{i,jk}^{-1/\psi} = \tilde{p}_{jk} \tau_{ji} L_i \\ & \frac{-\eta_i}{L_i} \kappa_k^{\frac{1}{\sigma}} c_i^{\frac{1}{\sigma}} c_{ik}^{\frac{\sigma-\psi}{\sigma\psi}} c_{i,jk}^{-1/\psi} = \tilde{p}_{jk} \tau_{ji}.\end{aligned} \tag{A.63}$$

This allows us to also determine a price index $\tilde{P}_i$ for the planner:

$$\begin{aligned}
&\frac{-\eta_i}{L_i}\kappa_k^{\frac{1}{\sigma}} c_i^{\frac{1}{\sigma}} c_{ik}^{\frac{\sigma-\psi}{\sigma\psi}} c_{i,jk}^{\frac{\psi-1}{\psi}} = \tilde{p}_{jk}\tau_{ji}c_{i,jk} \\
\rightarrow &\frac{-\eta_i}{L_i}\kappa_k^{\frac{1}{\sigma}} c_i^{\frac{1}{\sigma}} c_{ik}^{\frac{\sigma-\psi}{\sigma\psi}} \sum_j c_{i,jk}^{\frac{\psi-1}{\psi}} = \sum_j \tilde{p}_{jk}\tau_{ji}c_{i,jk} \\
\rightarrow &\frac{-\eta_i}{L_i}\kappa_k^{\frac{1}{\sigma}} c_i^{\frac{1}{\sigma}} c_{ik}^{\frac{\sigma-\psi}{\sigma\psi}} c_{ik}^{\frac{\psi-1}{\psi}} = \sum_j \tilde{p}_{jk}\tau_{ji}c_{i,jk} \\
\rightarrow &\frac{-\eta_i}{L_i}\kappa_k^{\frac{1}{\sigma}} c_i^{\frac{1}{\sigma}} c_{ik}^{\frac{\sigma-1}{\sigma}} = \sum_j \tilde{p}_{jk}\tau_{ji}c_{i,jk} \\
\rightarrow &\frac{-\eta_i}{L_i} c_i^{\frac{1}{\sigma}} \sum_k \kappa_k^{\frac{1}{\sigma}} c_{ik}^{\frac{\sigma-1}{\sigma}} = \sum_k \sum_j \tilde{p}_{jk}\tau_{ji}c_{i,jk} \\
\rightarrow &\frac{-\eta_i}{L_i} c_i^{\frac{1}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = \sum_k \sum_j \tilde{p}_{jk}\tau_{ji}c_{i,jk} \\
\rightarrow &\frac{-\eta_i}{L_i} c_i = \sum_k \sum_j \tilde{p}_{jk}\tau_{ji}c_{i,jk},
\end{aligned}$$

which defines:

$$\begin{aligned}
\tilde{P}_i := \frac{-\eta_i}{L_i} &= \left(\sum_k \left(\sum_j (\tilde{p}_{jk}\tau_{ji})^{1-\psi}\right)^{\frac{1-\sigma}{1-\psi}}\right)^{\frac{1}{1-\sigma}} \\
&= \left(\sum_k \tilde{P}_{ik}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}
\end{aligned}$$

Plugging this into equation (A.63) and manipulating, we get

$$\tau_{ji}\tilde{p}_{jk}c_{i,jk} = \kappa_k \frac{(\tau_{ji}\tilde{p}_{jk})^{1-\psi}\tilde{P}_{ik}^{\psi-\sigma}}{\tilde{P}_i^{1-\sigma}}\tilde{P}_i c_i. \tag{A.64}$$

Further, consider the allocation of land across sectors within a region:

$$\{H_{ik}\} : \tilde{p}_{ik} z_{ik}^{\iota} f_{k,2} = \tilde{r}_i.$$

This implies that for allocations across any two sectors $\{k, k'\}$, we would require:

$$\begin{aligned}\tilde{p}_{ik} z_{ik}^{\iota} f'_{k,2} &= \tilde{r}_i = \tilde{p}_{ik'} z_{ik'}^{\iota} f'_{k',2} \\ \tilde{p}_{ik} z_{ik}^{\iota} f'_{k,2} &= \tilde{p}_{ik'} z_{ik'}^{\iota} f'_{k',2}. \end{aligned} \tag{A.65}$$

Now, consider the allocation for workers across regions:

$$\begin{aligned}\{L_i\} : \Gamma(\frac{\nu-1}{\nu}) W^{1-\nu} (a_i c_i)^{\nu-1} c_i \frac{\partial a_i}{\partial L_i} + \mu_i + \tilde{w}_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} = 0 \\ \rightarrow \Gamma(\frac{\nu-1}{\nu}) W^{1-\nu} a_i^{\nu-1} c_i^{\nu} \frac{\frac{\partial a_i}{a_i}}{\frac{\partial L_i}{L_i}} \frac{a_i}{L_i} + \mu_i + \tilde{w}_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} = 0 \\ \rightarrow \ -\Gamma(\frac{\nu-1}{\nu}) W^{1-\nu} (a_i c_i)^{\nu} \theta L_i^{-1} + \mu_i + \tilde{w}_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} = 0 \\ \rightarrow \ -\Gamma(\frac{\nu-1}{\nu}) W^{1-\nu} (a_i c_i)^{\nu} \theta \frac{W^{\nu}}{(a_i c_i)^{\nu}} + \mu_i + \tilde{w}_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} = 0 \\ \rightarrow \ -\Gamma(\frac{\nu-1}{\nu}) W\theta + \mu_i + \tilde{w}_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} = 0 \\ \rightarrow \mu_i = \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} - \tilde{w}_i + \Gamma(\frac{\nu-1}{\nu}) W\theta, \end{aligned} \tag{A.66}$$

where note that $\tilde{w}_i$ represents the social marginal product of worker per region in contrast to w_i which is the competitive wage reflecting the private marginal product per worker.

Now, note that the planner would always set landlord consumption in each region to 0. Taking first order conditions on landlord consumption, we get

$$\frac{\partial \mathcal{L}}{\partial c_{i,jk}^{l}} = -\tau_{ji} \tilde{p}_{jk} \leq 0$$

Allocating any consumption to the landlords purely acts as a marginal cost for the planner. As such, it is optimal to set landlord consumption to 0 in each region i for each region-sector

(j,k)'s goods, that is

$$c^L_{i,jk} = 0 \qquad \forall i,j,k \tag{A.67}$$

A4.1 Proof for optimal consumption in each region

Now, we determine optimal consumption c_i per worker across regions. Taking first order conditions with respect to c_i on (A.61), we obtain:

$$\begin{aligned}
&\Gamma(\frac{\nu-1}{\nu})W^{1-\nu}(a_ic_i)^{\nu-1}a_i + \eta_i = \mu_i\left(\frac{\nu(a_ic_i)^{\nu-1}a_i\bar{L}}{\sum_j(a_jc_j)^\nu} - \frac{(a_ic_i)^\nu\bar{L}}{(\sum_j(a_jc_j)^\nu)^2}\nu(a_ic_i)^{\nu-1}a_i\right) - \\
&\sum_{j\neq i} W_j\frac{(a_jc_j)^\nu\bar{L}}{(\sum_n(a_nc_n)^\nu)^2}\nu(a_ic_i)^{\nu-1}a_i \\
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{c_i}\frac{(a_ic_i)^\nu}{W^\nu} + \eta_i = \mu_i\frac{\nu(a_ic_i)^{\nu-1}a_i\bar{L}}{\sum_j(a_jc_j)^\nu}\left(1 - \frac{(a_ic_i)^\nu}{\sum_j(a_jc_j)^\nu}\right) \\
&-\sum_{j\neq i} W_j\frac{\nu(a_ic_i)^{\nu-1}a_i\bar{L}}{\sum_n(a_nc_n)^\nu}\frac{(a_jc_j)^\nu}{\sum_n(a_nc_n)^\nu} \\
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{L}\frac{L_i}{c_i} = -\eta_i + \nu\mu_i\frac{L_i}{c_i}\left(1-\frac{L_i}{L}\right) - \nu\frac{L_i}{c_i}\sum_{j\neq i}W_j\frac{L_j}{L} \\
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{L} = -\eta_i\frac{c_i}{L_i} + \nu\mu_i - \nu\sum_i\mu_i\frac{L_i}{L}
\end{aligned}$$

plugging in for μ_i from (A.66)

$$\begin{aligned}
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{L} + \nu\sum_i\mu_i\frac{L_i}{L} = \tilde{P}_ic_i + \nu\left(\sum_j\sum_k\tilde{p}_{jk}\tau_{ji}c_{i,jk} - \tilde{w}_i + \Gamma(\frac{\nu-1}{\nu})W\theta\right) \\
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{L} + \nu\sum_i\mu_i\frac{L_i}{L} + \nu\left(\tilde{w}_i - \Gamma(\frac{\nu-1}{\nu})W\theta\right) = (1+\nu)\tilde{P}_ic_i \\
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{L} + \nu\sum_i\frac{L_i}{L}\left(\sum_j\sum_k\tilde{p}_{jk}\tau_{ji}c_{i,jk} - \tilde{w}_i + \Gamma(\frac{\nu-1}{\nu})W\theta\right) + \\
&\nu\left(\tilde{w}_i - \Gamma(\frac{\nu-1}{\nu})W\theta\right) = (1+\nu)\tilde{P}_ic_i \\
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{L} + \nu\sum_i\frac{L_i}{L}(\tilde{P}_ic_i - \tilde{w}_i) + \nu\tilde{w}_i = (1+\nu)\tilde{P}_ic_i \\
\rightarrow\ &\Gamma(\frac{\nu-1}{\nu})\frac{W}{L(1+\nu)} + \frac{\nu}{1+\nu}\sum_i\frac{L_i}{L}(\tilde{P}_ic_i - \tilde{w}_i) + \frac{\nu}{1+\nu}\tilde{w}_i = \tilde{P}_ic_i.
\end{aligned} \tag{A.68}$$

Now, in order to build intuition on consumption, we need an expression for $\Gamma(\frac{\nu-1}{\nu})W$. Multiplying both sides by L_i and summing across regions:

$$\begin{aligned}
&\Gamma(\frac{\nu-1}{\nu})\frac{W}{(1+\nu)} + \frac{\nu}{1+\nu}\sum_i L_i(\tilde{P}_i c_i - \tilde{w}_i) + \frac{\nu}{1+\nu}\sum_i \tilde{w}_i L_i = \sum_i L_i \tilde{P}_i c_i \\
&\Gamma(\frac{\nu-1}{\nu})\frac{W}{(1+\nu)} + \frac{\nu}{1+\nu}\sum_i L_i(\tilde{P}_i c_i - \tilde{w}_i) + \frac{\nu}{1+\nu}\sum_i \tilde{w}_i L_i - \\
&\frac{\nu}{1+\nu}\sum_i L_i \tilde{P}_i c_i = \frac{1}{1+\nu}\sum_i L_i \tilde{P}_i c_i \\
&\Gamma(\frac{\nu-1}{\nu})W = \sum_i L_i \tilde{P}_i c_i. \qquad \text{(A.69)}
\end{aligned}$$

Then, we can write consumption spending per worker by plugging (A.69) in to (A.68):

$$\begin{aligned}
\tilde{P}_i c_i &= \frac{\sum_i L_i \tilde{P}_i c_i}{L(1+\nu)} + \frac{\nu}{1+\nu}\sum_i \frac{L_i}{L}(\tilde{P}_i c_i - \tilde{w}_i) + \frac{\nu}{1+\nu}\tilde{w}_i \\
&= \frac{\nu}{1+\nu}\tilde{w}_i + \frac{\sum_i L_i \tilde{P}_i c_i}{L} - \frac{\nu}{(1+\nu)L}\sum_{i=1}^{N} L_i \tilde{w}_i \\
&= \frac{\nu}{1+\nu}\tilde{w}_i + \underbrace{\frac{\sum_i L_i\Big((1+\nu)\tilde{P}_i c_i - \nu\tilde{w}_i\Big)}{(1+\nu)L}}_{=\Lambda} \\
&= \frac{\nu}{1+\nu}\tilde{w}_i + \Lambda, \qquad \text{(A.70)}
\end{aligned}$$

where the value of Λ is determined such that

$$\Gamma(\frac{\nu-1}{\nu})W = \sum_i L_i \tilde{P}_i c_i,$$

holds.

A4.2 Proof for Proposition 1

Now, consider the first order condition for allocating workers to any sector k in any region i:

$$\begin{aligned}
\{L_{ik}\} :& p_{ik} z_{ik}^{\iota} f'_{k,1} z_{ik}^{1-\iota} + p_{ik} z_{ik}^{\iota} f'_{k,1} \left(L_{ik}(1-\iota) z_{ik}^{-\iota} \frac{\partial z_{ik}}{\partial L_{ik}} \right) + \iota p_{ik} f_k \left(z_{ik}^{1-\iota} L_{ik}, H_{ik} \right) z_{ik}^{\iota-1} \frac{\partial z_{ik}}{\partial L_{ik}} = \tilde{w}_i \\
\rightarrow\ & p_{ik} z_{ik} f'_{k,1} + (1-\iota) p_{ik} f'_{k,1} \frac{\frac{\partial z_{ik}}{z_{ik}}}{\frac{\partial L_{ik}}{L_{ik}}} z_{ik} + \iota p_{ik} f_k \left(z_{ik}^{1-\iota} L_{ik}, H_{ik} \right) z_{ik}^{\iota-1} \frac{\frac{\partial z_{ik}}{z_{ik}}}{\frac{\partial L_{ik}}{L_{ik}}} \frac{z_{ik}}{L_{ik}} = \tilde{w}_i \\
\rightarrow\ & p_{ik} z_{ik} f'_{k,1} + (1-\iota) p_{ik} z_{ik} f'_{k,1} \phi_k + \iota \phi_k \frac{p_{ik} z_{ik} f_k \left(z_{ik}^{1-\iota} L_{ik}, H_{ik} \right)}{L_{ik}} z_{ik}^{\iota-1} = \tilde{w}_i \\
\rightarrow\ & p_{ik} z_{ik} f'_{k,1} \left(1 + (1-\iota)\phi_k \right) + \iota z_{ik}^{\iota-1} \phi_k y_{ik} = \tilde{w}_i .
\end{aligned}$$

Since the social planner equalizes the marginal value added from a worker across all sectors within a region, we get:

$$\begin{aligned}
p_{ik} z_{ik} f'_{k,1} \left(1 + (1-\iota)\phi_k \right) + \iota z_{ik}^{\iota-1} \phi_k y_{ik} = w_i = p_{ik'} z_{ik'} f'_{k',1} \left(1 + (1-\iota)\phi_{k'} \right) + \iota z_{ik'}^{\iota-1} \phi_{k'} y_{ik'} \\
\Rightarrow\ p_{ik} z_{ik} f'_{k,1} \left(1 + (1-\iota)\phi_k \right) + \iota \phi_k y_{ik} = p_{ik'} z_{ik'} f'_{k',1} \left(1 + (1-\iota)\phi_{k'} \right) + \iota \phi_{k'} y_{ik'} .
\end{aligned} \tag{A.71}$$

Consider how this equation evolves conditional on the value for $\iota \in \{0, 1\}$:

$$\text{For } \iota = 0 : p_{ik} z_{ik} f'_{k,1} (1 + \phi_k) = p_{ik'} z_{ik'} f'_{k',1} (1 + \phi_{k'}).$$

$$\text{For } \iota = 1 : p_{ik} z_{ik} f'_{k,1} + \phi_k y_{ik} = p_{ik'} z_{ik'} f'_{k',1} + \phi_{k'} y_{ik'} .$$

A4.3 Extension with regional agglomeration

Now, we have productivity in a region-sector $z_{ik} = \bar{z}_{ik} L_{ik}^{\phi_k} L_i^{\phi}$. This changes the first order condition for workers L_i in a region:

$$
\begin{aligned}
\{L_i\} : \mu_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} + \tilde{w}_i - \Gamma(\frac{\nu-1}{\nu}) W\theta + \\
\sum_k \left(p_{ik} z_{ik}^{\iota} f'_{k,1} \left(L_{ik}(1-\iota) z_{ik}^{-\iota} \frac{\partial z_{ik}}{\partial L_i} \right) + \iota p_{ik} f_k \left(z_{ik}^{1-\iota} L_{ik}, H_{ik} \right) z_{ik}^{\iota-1} \frac{\partial z_{ik}}{\partial L_i} \right) = 0 \\
\rightarrow \mu_i - \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} + \tilde{w}_i - \Gamma(\frac{\nu-1}{\nu}) W\theta + (1-\iota)\phi\tilde{w}_i + \iota \frac{\phi}{L_i} \sum_k p_{ik} z_{ik} f_k \left(L_{ik}, H_{ik} \right) = 0 \\
\rightarrow \mu_i = \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} + \Gamma(\frac{\nu-1}{\nu}) W\theta - \tilde{w}_i - (1-\iota)\phi\tilde{w}_i - \iota \frac{\phi}{L_i} \sum_k p_{ik} z_{ik} f_k \left(L_{ik}, H_{ik} \right) \\
\rightarrow \mu_i = \sum_j \sum_k p_{jk} \tau_{ji} c_{i,jk} + \Gamma(\frac{\nu-1}{\nu}) W\theta - (1 + (1-\iota)\phi)\tilde{w}_i - \iota\phi y_i,
\end{aligned}
$$

where $y_i = \frac{1}{L_i} \sum_k p_{ik} z_{ik} f_k \left(L_{ik}, H_{ik} \right)$, which is the sum of total value of output produced in a given region per worker.

The treatment for optimal consumption remains the same but gets augmented by this term depending on the value of ι. The first order conditions for sectoral labor and land allocations remain the same. Optimal consumption now is given by

$$
\begin{aligned}
\rightarrow \Gamma(\frac{\nu-1}{\nu}) \frac{W}{L(1+\nu)} + \frac{\nu}{1+\nu} \sum_i \frac{L_i}{L} \left(\tilde{P}_i c_i - \tilde{w}_i(1 + (1-\iota)\phi) - \iota\phi y_i \right) \\
+ \frac{\nu}{1+\nu} \left(\tilde{w}_i(1 + (1-\iota)\phi + \iota y_i \right) = \tilde{P}_i c_i.
\end{aligned}
$$

Summing across regions i, we get

$$
\Gamma(\frac{\nu-1}{\nu}) W = \sum_i L_i \tilde{P}_i c_i.
$$

Plugging into the previous expression, we get

$$\begin{aligned}\tilde{P}_i c_i &= \frac{\sum_i L_i \tilde{P}_i c_i}{L(1+\nu)} + \frac{\nu}{1+\nu}\sum_i \frac{L_i}{L}(\tilde{P}_i c_i - \tilde{w}_i) + \frac{\nu}{1+\nu}\tilde{w}_i \\ &= \frac{\nu}{1+\nu}\Big(\tilde{w}_i(1+(1-\iota)\phi) + \iota\phi y_i\Big) + \underbrace{\frac{\sum_i L_i\Big((1+\nu)\tilde{P}_i c_i - \nu((1+(1-\iota)\phi\tilde{w}_i + \iota\phi y_i)\Big)}{(1+\nu)L}}_{=\Lambda} \\ &= \frac{\nu}{1+\nu}\Big(\tilde{w}_i(1+(1-\iota)\phi) + \iota\phi y_i\Big) + \Lambda\end{aligned}$$

A4.4 Extension with migration costs

We solved for the planner for the sub-case with no migration costs, we can now extend this to the case where we do have migration costs. The first order conditions for for worker and land allocation across sectors remain unchanged. But consider workers across regions:

$$\begin{aligned}\{L_i\} : \Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j L_j^0 W_j^{1-\nu}\left(\frac{a_i c_i}{\mu_{ji}}\right)^{\nu-1}\frac{c_i}{\mu_{ji}}\frac{\partial a_i}{\partial L_i} + \chi_i + w_i - \sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk} = 0 \\ \Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j L_j^0 W_j^{1-\nu}\left(\frac{a_i c_i}{\mu_{ji}}\right)^{\nu-1}\frac{c_i}{\mu_{ji}}\frac{\partial a_i/a_i}{\partial L_i/L_i}\frac{a_i}{L_i} + \chi_i + w_i - \sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk} = 0 \\ -\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j L_j^0 W_j^{1-\nu}\left(\frac{a_i c_i}{\mu_{ji}}\right)^{\nu}\theta\frac{1}{L_i} + \chi_i + w_i - \sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk} = 0 \\ -\Gamma(\frac{\nu-1}{\nu})\frac{\theta}{L_i}\sum_j \alpha_j W_j \Pi_{ji} + \chi_i + w_i - \sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk} = 0 \\ -\Gamma_i\theta + \chi_i + w_i - \sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk} = 0\end{aligned}$$

where $\Gamma_i = \Gamma(\frac{\nu-1}{\nu})\frac{1}{L_i}\sum_j \alpha_j W_j \Pi_{ji}$. This allows us to determine the marginal value of a worker in a given region:

$$\chi_i = \sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk} - w_i + \Gamma_i\theta \tag{A.72}$$

Consider now the first order conditions for C_i:

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j L_j^0 W_j^{1-\nu}\left(\frac{a_i c_i}{\mu_{ji}}\right)^{\nu-1}\frac{a_i}{\mu_{ji}}+\eta_i=\Upsilon_i$$

where Υ_i is given:

$$\begin{aligned}
&\to \chi_i\left(\sum_j\left(\frac{\nu(\frac{a_i c_i}{\mu_{ji}})^{\nu-1}\frac{a_i}{\mu_{ji}}L_j^0}{W_j^\nu}-\frac{(\frac{a_i c_i}{\mu_{ji}})^\nu L_j^0}{(W_j^\nu)^2}\nu(\frac{a_i c_i}{\mu_{ji}})^{\nu-1}\frac{a_i}{\mu_{ji}}\right)\right)\\
&\quad+\sum_{j\neq i}\chi_j\sum_{n=1}^{N}\left(-\frac{(\frac{a_j c_j}{\mu_{nj}})^\nu L_n^0}{(W_n^\nu)^2}\nu(\frac{a_i c_i}{\mu_{ni}})^{\nu-1}\frac{a_i}{\mu_{ni}}\right)\\
&\to \chi_i\sum_{j=1}^{N}\frac{1}{c_i}\frac{\nu(\frac{a_i c_i}{\mu_{ji}})^\nu L_j^0}{W_j^\nu}\left(1-\frac{\Pi_{ji}}{L_j^0}\right)-\sum_{j\neq 1}\chi_j\sum_{n=1}^{N}\frac{1}{c_i}\frac{\nu(\frac{a_i c_i}{\mu_{ni}})^\nu L_n^0}{W_n^\nu}\frac{\Pi_{nj}}{L_n^0}\\
&\to \nu\frac{\chi_i}{c_i}\sum_{j=1}^{N}\Pi_{ji}-\frac{\nu}{c_i}\sum_j\chi_j\sum_{n=1}^{N}\Pi_{ni}\frac{\Pi_{nj}}{L_n^0}\\
&\to \nu\chi_i\frac{L_i}{c_i}-\frac{\nu}{c_i}\sum_j\chi_j\sum_{n=1}^{N}\Pi_{ni}\frac{\Pi_{nj}}{L_n^0}
\end{aligned}$$

Plugging Υ_i back into the first order condition for C_i

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j L_j^0 W_j^{1-\nu}\left(\frac{a_i c_i}{\mu_{ji}}\right)^{\nu-1}\frac{a_i}{\mu_{ji}}+\eta_i=\nu\chi_i\frac{L_i}{c_i}-\frac{\nu}{c_i}\sum_j\chi_j\sum_{n=1}^{N}\Pi_{ni}\frac{\Pi_{nj}}{L_n^0}$$

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j L_j^0 W_j^{1-\nu}\left(\frac{a_i c_i}{\mu_{ji}}\right)^{\nu}\frac{1}{c_i}+\eta_i=\nu\chi_i\frac{L_i}{c_i}-\frac{\nu}{c_i}\sum_j\chi_j\sum_{n=1}^{N}\Pi_{ni}\frac{\Pi_{nj}}{L_n^0}$$

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j W_j\frac{\Pi_{ji}}{c_i}+\eta_i=\nu\chi_i\frac{L_i}{c_i}-\frac{\nu}{c_i}\sum_j\chi_j\sum_{n=1}^{N}\Pi_{ni}\frac{\Pi_{nj}}{L_n^0}$$

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j W_j\frac{\Pi_{ji}}{c_i}+\frac{\nu}{c_i}\sum_j\chi_j\sum_{n=1}^{N}\Pi_{ni}\frac{\Pi_{nj}}{L_n^0}=-\eta_i+\nu\chi_i\frac{L_i}{c_i}$$

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j W_j\frac{\Pi_{ji}}{L_i}+\frac{\nu}{L_i}\sum_j\chi_j\sum_{n=1}^{N}\Pi_{ni}\frac{\Pi_{nj}}{L_n^0}=p_i c_i+\nu\chi_i$$

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j W_j\frac{\Pi_{ji}}{L_i}+\frac{\nu}{L_i}\sum_j\chi_j\psi_{ij}=p_i c_i+\nu(p_i c_i-\mu_i-\Gamma_i\theta)$$

$$\Gamma(\frac{\nu-1}{\nu})\sum_{j=1}^{N}\alpha_j W_j\frac{\Pi_{ji}}{L_i}+\frac{\nu}{L_i}\sum_j\psi_{ij}(p_j c_j-\mu_j-\Gamma_j\theta)+\nu\mu_i+\nu\Gamma_i\theta=(1+\nu)p_i c_i$$

$$\Omega_i+\frac{\nu}{L_i(1+\nu)}\sum_j\psi_{ij}(p_j c_j-\mu_j)+\frac{\nu\theta}{1+\nu}(\Gamma_i-\sum_j\psi_{ij}\Gamma_j)+\frac{\nu}{1+\nu}\mu_i=p_i c_i$$

A4.5 Extension with heterogeneous congestion

Now, we have amenities in a region $a_i=\bar{a}_i L_i^{-\theta_i}$. This changes the first order condition for workers L_i in a region:

$$\{L_i\}:\mu_i-\sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk}+\tilde{w}_i-\Gamma(\frac{\nu-1}{\nu})W\theta_i=0$$

$$\mu_i=\sum_j\sum_k p_{jk}\tau_{ji}c_{i,jk}+\Gamma(\frac{\nu-1}{\nu})W\theta_i-\tilde{w}_i.$$

Optimal consumption comes down to be written as

$$\begin{aligned}
&\to \Gamma(\frac{\nu-1}{\nu})\frac{W}{L} + \nu\sum_i \frac{L_i}{L}\left(\sum_j\sum_k \tilde{p}_{jk}\tau_{ji}c_{i,jk} - \tilde{w}_i + \Gamma(\frac{\nu-1}{\nu})W\theta\right) + \nu\left(\tilde{w}_i - \Gamma(\frac{\nu-1}{\nu})W\theta\right) \\
&\quad = (1+\nu)\tilde{P}_i c_i \\
&\to \Gamma(\frac{\nu-1}{\nu})\frac{W}{L} + \nu\sum_i \frac{L_i}{L}(\tilde{P}_i c_i - \tilde{w}_i) + \nu\tilde{w}_i + \nu\Gamma(\frac{\nu-1}{\nu})W\left(\sum_i \frac{L_i}{L}\theta_i - \theta_i\right) = (1+\nu)\tilde{P}_i c_i \\
&\to \Gamma(\frac{\nu-1}{\nu})\frac{W}{L(1+\nu)} + \frac{\nu}{1+\nu}\sum_i \frac{L_i}{L}(\tilde{P}_i c_i - \tilde{w}_i) + \frac{\nu}{1+\nu}\tilde{w}_i + \frac{\nu}{1+\nu}\Gamma(\frac{\nu-1}{\nu})W\left(\sum_i \frac{L_i}{L}\theta_i - \theta_i\right) \\
&\quad = \tilde{P}_i c_i.
\end{aligned}$$

Now, summing across regions i, we once again obtain

$$\Gamma(\frac{\nu-1}{\nu})W = \sum_i L_i \tilde{P}_i c_i.$$

Plugging into the previous expression, we get

$$\begin{aligned}
\tilde{P}_i c_i &= \frac{\sum_i L_i \tilde{P}_i c_i}{L(1+\nu)} + \frac{\nu}{1+\nu}\sum_i \frac{L_i}{L}(\tilde{P}_i c_i - \tilde{w}_i) + \frac{\nu}{1+\nu}\tilde{w}_i + \frac{\nu}{1+\nu}\Gamma(\frac{\nu-1}{\nu})W\left(\sum_i \frac{L_i}{L}\theta_i - \theta_i\right) \\
&= \frac{\nu}{1+\nu}\tilde{w}_i + \underbrace{\frac{\sum_i L_i\left((1+\nu)\tilde{P}_i c_i - \nu\tilde{w}_i\right)}{(1+\nu)L}}_{=\Lambda} + \frac{\nu}{1+\nu}\Gamma(\frac{\nu-1}{\nu})W\left(\sum_i \frac{L_i}{L}\theta_i - \theta_i\right) \\
&= \frac{\nu}{1+\nu}\tilde{w}_i + \Lambda + R_i
\end{aligned}$$

where

$$R_i = \frac{\nu}{1+\nu}\Gamma(\frac{\nu-1}{\nu})W\left(\sum_i \frac{L_i}{L}\theta_i - \theta_i\right)$$

A5 Implementation of Planner Solution

A5.1 Proof for Proposition 2

I now discuss the implementation of the planner solution. One possibility is to offer subsidies to the targeted sector (S_{ik}), combined with a constant income tax on workers everywhere (t_L) and a transfer (Λ).

Consider an ad-valorem wage subsidy $s_k = \frac{(1-\iota)\phi_k}{1+(1-\iota)\phi_k}$ alongside a per-worker subsidy $s_{ik} = \frac{\iota\phi_k}{1+(1-\iota)\phi_k}\frac{p_{ik}q_{ik}}{L_{ik}}$. I consider the optimal worker and land choice for a given sector k in region i, by aggregating firms to a sector level exploiting CRS production and identical firms.

$$\pi = \max_{L_{ik},H_{ik}} \; p_{ik}z_{ik}^{\iota}f_k(z_{ik}^{1-\iota}L_{ik}, H_{ik}) - \Big(w_i(1-s_k) - s_{ik}\Big)L_{ik} - r_iH_{ik}.$$

The first-order conditions for workers is now

$$\begin{aligned}
\{L_{ik}\} :& p_{ik}z_{ik}f'_{k,1} = (1-s_k)w_i - s_{ik} \\
&\rightarrow \frac{p_{ik}z_{ik}f'_{k,1} + s_{ik}}{1-s_k} = w_i \\
&\rightarrow p_{ik}z_{ik}f'_{k,1}\Big(1+(1-\iota)\phi_k\Big) + \frac{\Big(1+(1-\iota)\phi_k\Big)}{\Big(1+(1-\iota)\phi_k\Big)}\iota\phi_k\frac{p_{ik}q_{ik}}{L_{ik}} = w_i \\
&\rightarrow p_{ik}z_{ik}f'_{k,1}\Big(1+(1-\iota)\phi_k\Big) + \iota\phi_k\frac{p_{ik}q_{ik}}{L_{ik}} = w_i. \qquad \text{(A.73)}
\end{aligned}$$

As such, the allocation of workers across sectors condition (1.2) in the equilibrium now satisfies:

$$p_{ik}z_{ik}f'_{k,1}\Big(1+(1-\iota)\phi_k\Big) + \iota\phi_k\frac{p_{ik}q_{ik}}{L_{ik}} = p_{ik'}z_{ik'}f'_{k',1}\Big(1+(1-\iota)\phi_{k'}\Big) + \iota\phi_{k'}\frac{p_{ik'}q_{ik'}}{L_{ik'}}. \qquad \text{(A.74)}$$

Define total subsidy for a given region-sector as

$$S_{ik} = s_{ik}L_{ik} + s_k w_i L_{ik}$$

The subsidies are financed by taxes on local landlords such that budget balances within each region.

$$\sum_k S_{ik} = t_i^H r_i H_i \qquad \forall i \tag{A.75}$$

Note that taxing local landlords to fund the local industrial subsidies does not entail a cross-regional transfer, and as such, industrial subsidies remain locally financed.

The remaining rental income in each region is then taxed entirely and transferred lump sum T to workers everywhere such that

$$T\bar{L} = \sum_i (1 - t_i^H) r_i H_i$$

This implies that landlord consumption in each region i is

$$c_{i,jk}^L = 0 \qquad \forall j, k \tag{A.76}$$

Now, directly taxing workers $t_L = \frac{1}{1+\nu}$ and offering transfers Λ implies that consumption for each worker in each region satisfies:

$$\sum_j \sum_k p_{i,jk} c_{i,jk} = (1 - t_L) w_i + \Lambda$$

$$P_i c_i = \frac{\nu}{1+\nu} w_i + \Lambda, \tag{A.77}$$

where the transfer has to be such that the budget balances:

$$\Lambda = \frac{t_L \sum_i \tilde{w}_i L_i}{L} + \frac{T}{L} \tag{A.78}$$

An equilibrium with taxes and transfers is defined as the equilibrium without taxes and transfers but with additional constraints that: i) I_i is given by (A.77), ii) the condition for allocation of workers across sectors in each region is given by either (A.74), iii) budget balances for industrial policy (A.75) , and iv) budget balances for consumption tax and transfer (A.78).

Then, the equilibrium with taxes and transfers implements the optimal allocation.

1. The optimal consumption for a region-sector (j, k) in equilibrium (A.33) is the same as the optimal consumption for a region-sector (j, k) in the planner solution (A.64).

2. The landlord consumption in equilibrium (A.76) is the same as in the planner solution (A.67).

3. The local budget constraint after taxes and transfer (A.77) implies a relationship between consumption and prices identical to (A.70), since wages in the equilibrium satisfy (A.73) and internalize the social marginal product of workers.

4. The optimal migration decision by households (1.7) is identical to the labor supply constraint in each region for the planner (A.58).

5. The allocation of land across sectors in each region in the competitive equilibrium (1.3) is identical to the optimal land allocation condition for the planner (A.65).

6. The allocation of workers across sectors in each region in the competitive equilibrium (A.74) is identical to the optimal labor allocation condition for the planner (A.71).

7. The market clearing conditions for output (1.8), labor allocation across sectors (1.9), and land market clearing (1.10) in the competitive equilibrium are identical to the

planner's resource constraints (A.57, A.60, A.59, A.56).

8. In the planner's solution, equation (A.69) has to hold.

A5.2 Proof for Proposition 3

When firms in the targeted sector are offered a uniform wage subsidy $\frac{\phi}{1+\phi}$, their optimal labor hiring decision is given:

$$p_{ik} z_{ik} f'_{k,1}(1+\phi) = w_i.$$

As such, the labor allocation in the equilibrium is given:

$$p_{ik} z_{ik} f'_{k,1}(1+\phi) = p_{ik'} z_{ik'} f'_{k',1}$$

When $\iota = 0$, this recovers the first-best. However, consider what happens when $\iota > 0$. The optimal allocation condition is given by:

$$p_{ik} z_{ik} f'_{k,1}\Big(1 + (1-\iota)\phi\Big) + \iota\phi y_{ik} = p_{ik'} z_{ik'} f'_{k',1}$$

In the decentralized equilibrium with the wage subsidy, the marginal returns to the targeted sector k are still positive since:

$$\begin{aligned}
& z_{ik} f'_{k,1} < \frac{q_{ik}}{L_{ik}} \\
\rightarrow\ & \iota\phi p_{ik} z_{ik} f'_{k,1} < \iota\phi \frac{p_{ik} q_{ik}}{L_{ik}} \\
\rightarrow\ & p_{ik} z_{ik} f'_{k,1}\Big(1 + (1-\iota)\phi\Big) + \iota\phi p_{ik} z_{ik} f'_{k,1} < p_{ik} z_{ik} f'_{k,1}\Big(1 + (1-\iota)\phi\Big) + \iota\phi y_{ik} \\
\Rightarrow\ & p_{ik} z_{ik} f'_{k,1}(1+\phi) < p_{ik} z_{ik} f'_{k,1}\Big(1 + (1-\iota)\phi\Big) + \iota\phi_k y_{ik},
\end{aligned}$$

Where the left hand side is the marginal returns captured by the decentralized equilibrium while the right hand side is the social marginal returns to the targeted sector k. Since the social marginal returns to the targeted sector k exceed the returns in the decentralized allocation for all $\iota \in [0, 1]$, we know that the welfare gains are positive since the subsidies push more workers to sector k but stays below the optimal level.

A6 Quantification

A6.1 Model: Calibrated parameters and values

Table A1: Model Parameters: Values and Sources

Parameter	**Description**	**Value**	**Source**
α_m	Labor share in manufacturing	0.55	Labor share in value added in manufacturing
α_o	Labor share in others	0.62	Labor share in value added overall
κ_m	Manufacturing preference share	0.09	Manufacturing share in value added
ν	Fréchet shape parameter (migration)	3.0	Bryan and Morten (2019)
σ	Elasticity of substitution (sectors)	2.8	Head and Mayer (2014)
ψ	Elasticity of substitution (regions)	3.8	Bajzik et al. (2020)

Continued on next page

Table A1 continued

Parameter	Description	Value	Source
γ	Elasticity of substitution (capital-labor)	2.0	Average across sources
θ	Amenity congestion elasticity	-0.6	Average across sources
ϕ_o	Other sectors agglomeration elasticity	0.0	Normalization
τ_{ij}	Bilateral trade costs	Varies	Calculated from distance using Redding (2016)
$\bar{a}_i$	Base amenities	Varies	Inverted from model
$\bar{z}_{im}$	Base manufacturing productivity	Varies	Inverted from model
$\bar{z}_{io}$	Base other sector productivity	Varies	Inverted from model

Notes: Parameters marked as "Inverted from model" are recovered using the structural relationships to match observed data. Standard calibrations follow common values in the spatial economics literature.

A6.2 Controls to account for underlying productivity

This section details the list of controls used to control for underlying productivities in each region:

1. **Ratio of High Skill Workers** This measures the ratio of workers with a level 4 qualification or above. A UK Level 4 qualification is a higher-education course equivalent to the first year of a bachelor's degree.
2. **Gender ratio** The ratio of males in the total regional population.
3. **Native ratio** The ratio of English workers in the total regional population.

4. **Temperature** The median TAS (temperature at surface) in the region between 2001-2020.

5. **Precipitation** The median precipitation rate (mm/day) in the region between 2001-2020.

6. **Number of summer days** The median number of summer days each year (defined as a day with max temperature above 25°C) between 2001-2020.

7. **Regional fixed effects** I add fixed effects for the following regions: i) North-East, ii) North-West, iii) South West, iv) South East, v) East of England, vi) Yorkshire and the Humber, vii) London, viii) West Midlands.

Table A2: Estimating Production Structure Parameter β - Full Results

	Adjusted Log Manufacturing Land	
	OLS	**IV**
Log Manufacturing Employment	1.087***	0.985***
	(0.100)	(0.125)
Skill Ratio	-2.687*	-2.958*
	(1.170)	(1.191)
Gender Ratio	20.521*	17.227
	(8.903)	(9.244)
Native Ratio	-0.561	-0.568
	(2.270)	(2.279)

	OLS	**IV**
Precipitation	0.324	0.433
	(0.933)	(0.940)
Summer Days	0.020	0.171
	(0.321)	(0.340)
Temperature	2.339	1.553
	(2.372)	(2.447)
Regional Fixed Effects	Yes	Yes
Observations	153	153
R^2	0.700	0.698
Weak instrument F-statistic	–	128.4

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Weak instrument F-statistic tests relevance of Polish immigrant populations. Standard errors in parentheses.

Table A3: Estimating agglomeration elasticity for manufacturing - Full Results

	Log Manufacturing Productivity	
	OLS	**IV**
Log Manufacturing Employment	0.186***	0.161***
	(0.020)	(0.025)

	OLS	IV
Skill Ratio	0.066	-0.018
	(0.235)	(0.241)
Gender Ratio	-3.153*	-3.716*
	(1.717)	(1.758)
Native Ratio	0.145	0.245
	(0.406)	(0.412)
Precipitation	-0.088	-0.061
	(0.120)	(0.122)
Summer Days	0.142**	0.177**
	(0.050)	(0.055)
Temperature	-2.474***	-2.665***
	(0.323)	(0.344)
Observations	153	153
R^2	0.778	0.776
Weak instrument F-statistic	–	274.5

Notes: ***$p < 0.01$, **$p < 0.01$, *$p < 0.05$. Weak instrument F-statistic tests relevance of Polish immigrant populations. Standard errors in parentheses.

A6.3 Robustness around γ

The robustness checks are presented here for alternative values of γ:

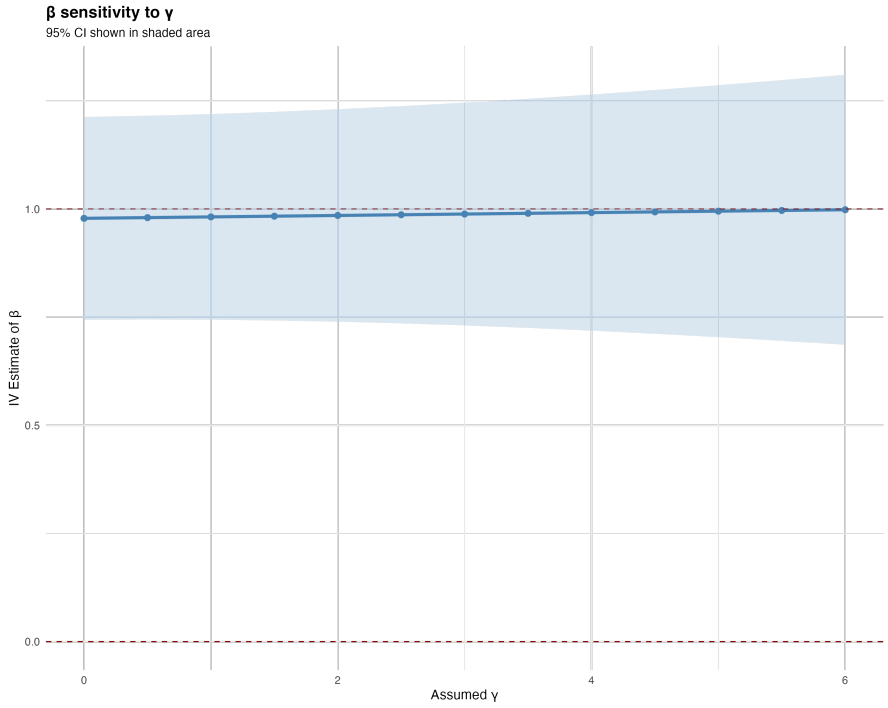


Figure A1: Estimated β for different values for γ

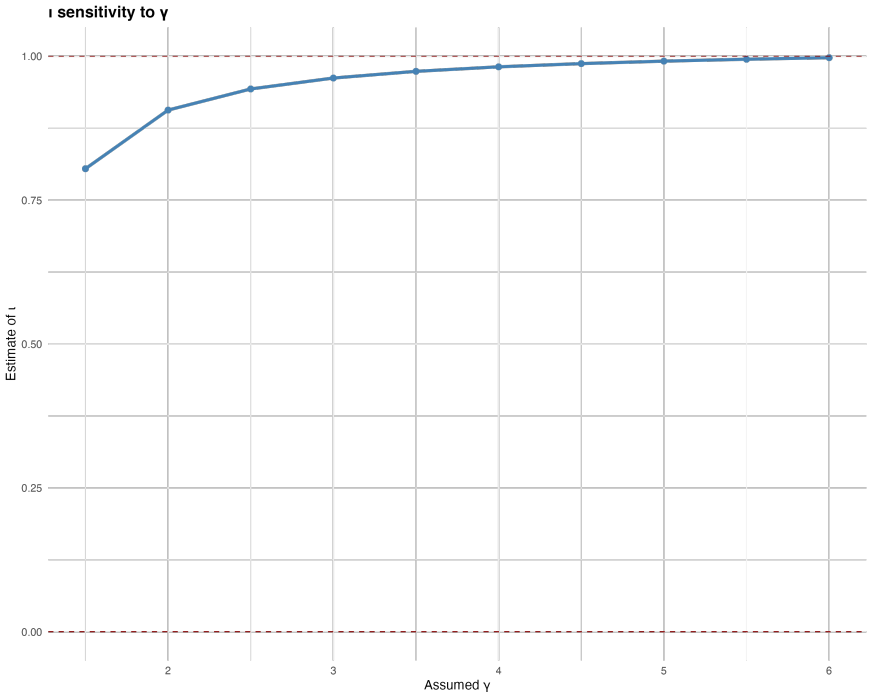


Figure A2: Changes in estimated ι for different values for γ

A6.4 A distribution for ι

The iterative procedure to obtain ι yields us a point estimate, but we can't account for uncertainty. In order to obtain a distribution for ι, I use a wild bootstrap first proposed by Wu (1986).

In order to account for potential heteroskedasticity when estimating β, we cannot run a standard bootstrap. A wild bootstrap randomly flips the signs from the error term in the original regression to yield a new sample thereby preserving the variance structure in the original sample. In order to obtain a distribution for ι, I then follow these steps:

1. Estimate β from (1.15) using the aforementioned IV procedure.

2. For each new draw of the sample, I randomly flip signs on the error terms from (1.15) to re-estimate β. I run a 1000 different simulations.

3. For each new values of the estimated β, I follow the procedure outlined in (1.4.4). This allows me account for the interdependence between ϕ_m and ι.

4. I obtain a 1000 values for the estimated ι using which I can plot CIs for ι^*.

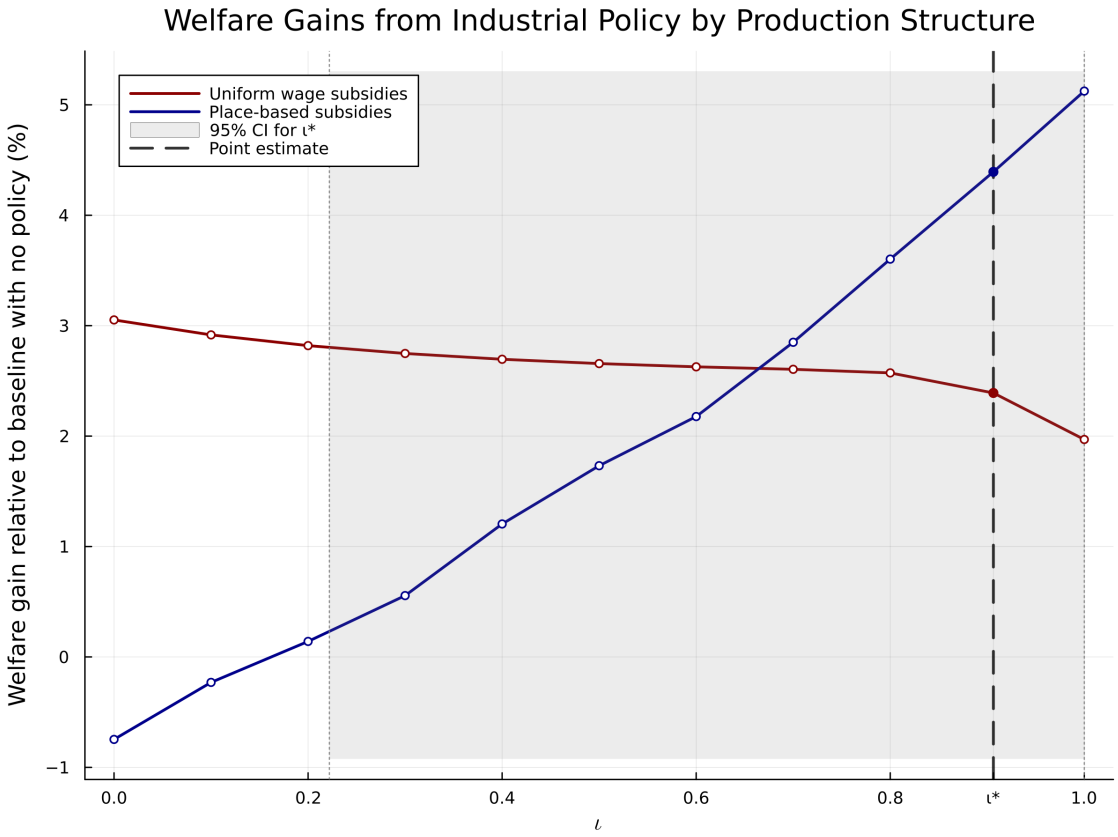


Figure A3: Confidence intervals for ι

Appendix B: The Economic Geography of Climate Risk

B1 Additional tables and figures

B1.1 Data: descriptive plots

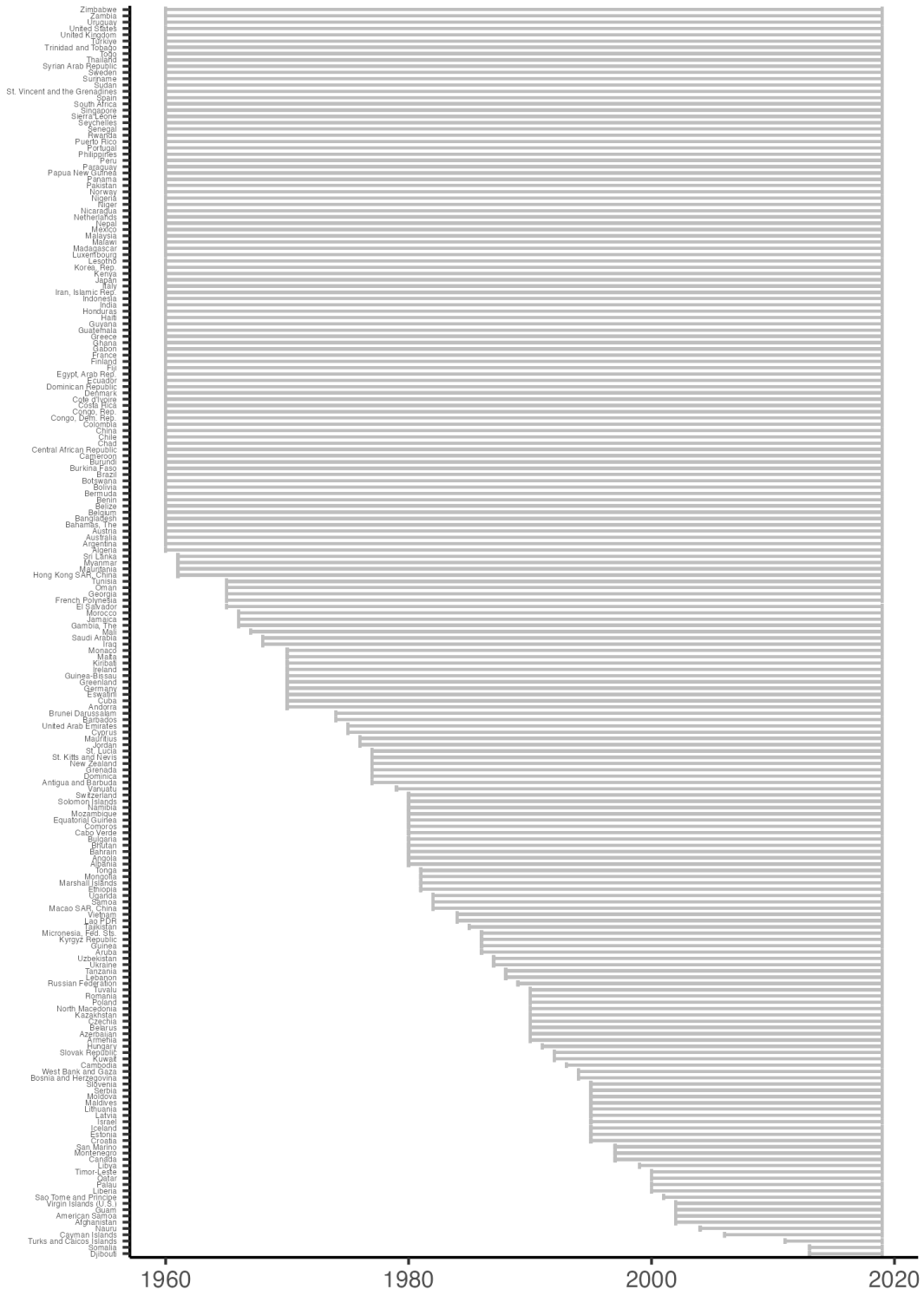


Figure B1: Years available in World Bank GDP-PC data.

B1.2 Additional results

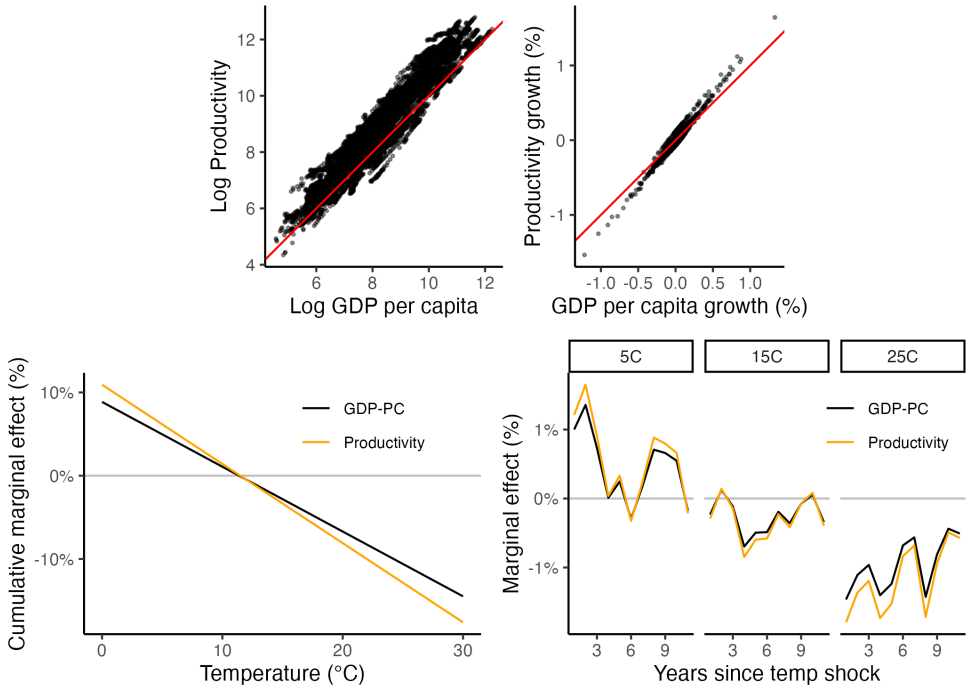


Figure B2: Comparison of damage function estimated on productivity to that estimated on GDP-PC.

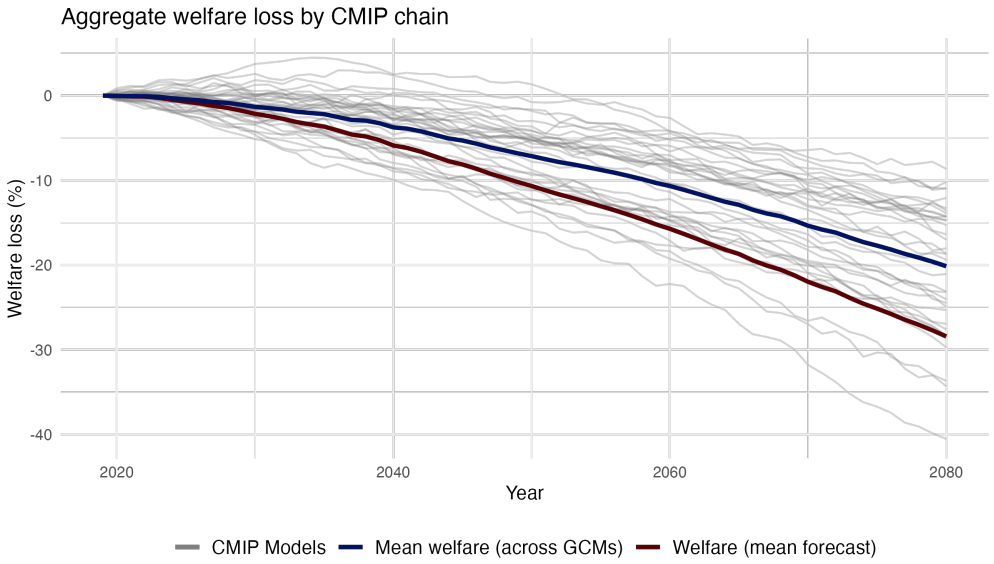


Figure B3: Global welfare loss $\ln \Upsilon_t - \ln \Upsilon_0$ under different CMIP models.

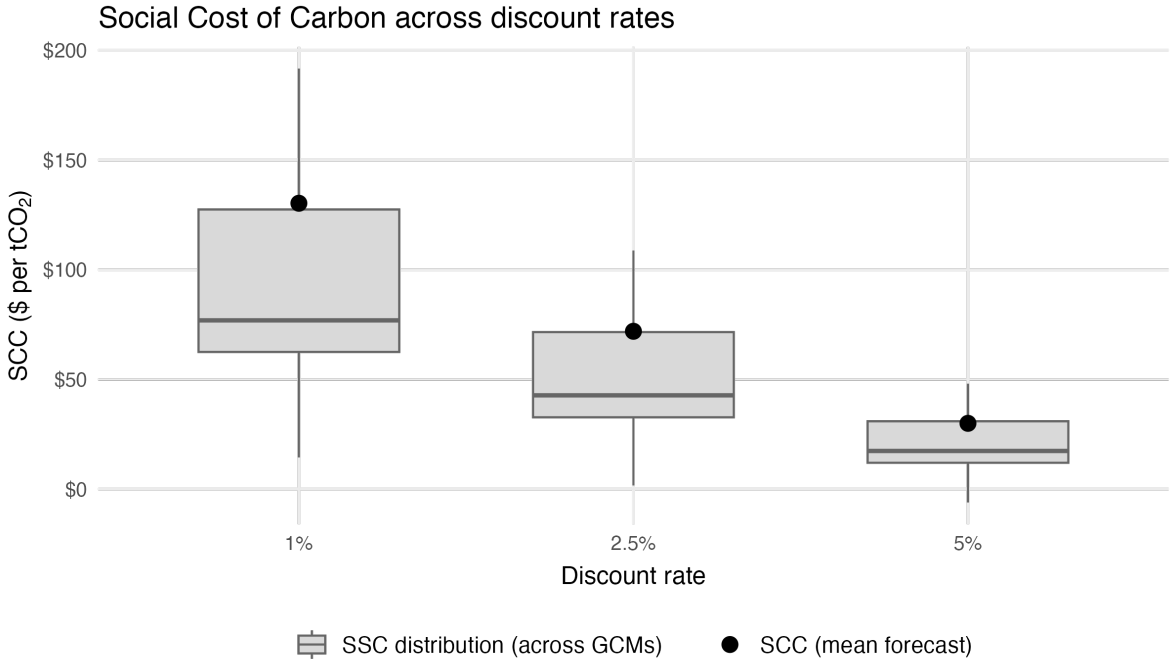


Figure B4: Distribution of SCC estimates for different discount rates.

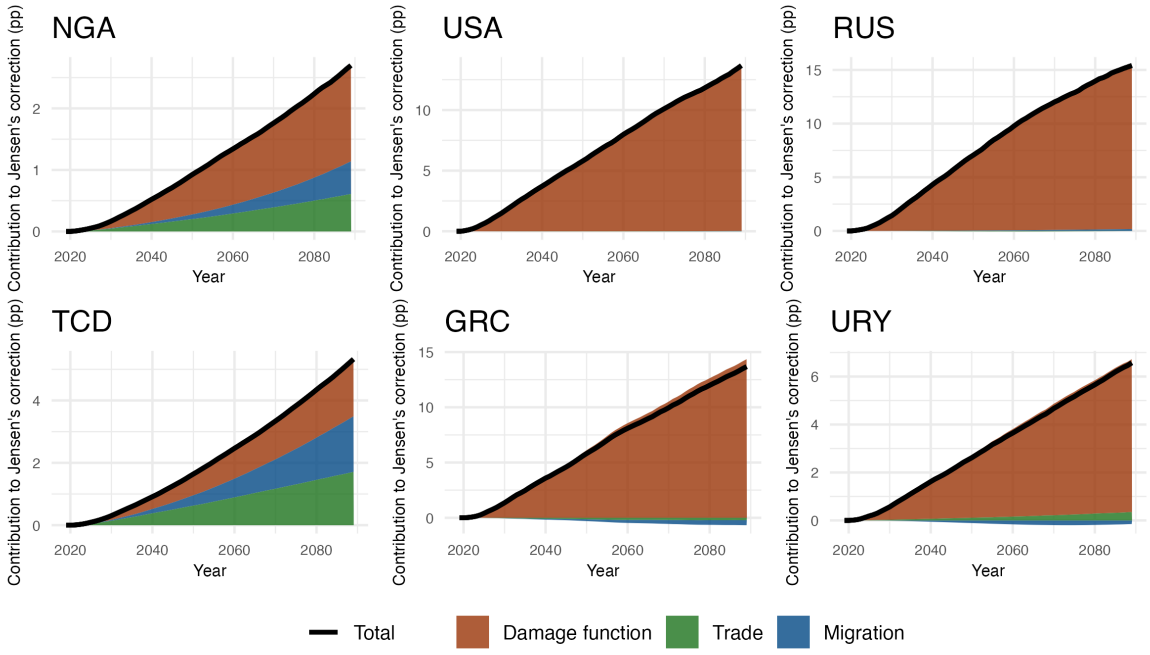

NGA
USA
RUS
TCD
GRC
URY
Contribution to Jensen's correction (pp)
Year
2020
2040
2060
2080
Total
Damage function
Trade
Migration

Figure B5

B1.3 Additional Tables

B2 Theory Appendix

In each period t, the model is described by several equations,

- Technology and factor price determination,

$$Y_d = Z_d L_d, \quad w_d = p_d Z_d$$

- Preferences which generate,

$$V_d = A_d \frac{w_d}{P_d}, \quad P_d = \left(\sum_o (\tau_{od} p_o)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

  and a notion of welfare,

$$\mathcal{W}_o = \left(\sum_d (V_d/\mu_{od})^\epsilon \right)^{1/\epsilon} = V_o \left(\sum_d \mu_{od}^{-\epsilon} (V_d/V_o)^\epsilon \right)^{1/\epsilon}$$

  as well as migration choice probabilities,

$$M_{od} = \frac{(V_d/\mu_{od})^\epsilon}{\sum_{d'} (V_{d'}/\mu_{od'})^\epsilon}$$

- and period-t market clearing,

$$L_{d,t} = \sum_o M_{od} L_{o,t-1}$$

  and,

$$p_o Y_o = \sum_d \left(\frac{\tau_{od} p_o}{P_d} \right)^{1-\sigma} p_d Y_d$$

B2.1 First-order decomposition

$d \ln Z$ shocks

Holding fixed amenity shocks $d \ln A_d = 0$, we start by log-differentiating welfare,

$$d \ln \mathcal{W}_o = \underbrace{d \ln V_o}_{\text{real income effect}} + \underbrace{\sum_d M_{od} \left(d \ln V_d - d \ln V_o \right)}_{\text{migration option value}}$$

Now,

$$d \ln V_d = \underbrace{d \ln Z_d}_{\text{direct effect}} + \underbrace{d \ln p_d - d \ln P_d}_{\text{trade effects}}$$

Now note,

$$d \ln P_d = \sum_o \underbrace{\left(\frac{\tau_{pd} p_o}{P_d} \right)^{1-\sigma}}_{\mathbf{T}_{od}} d \ln p_o$$

In matrix notation, this is $d \ln P = \mathbf{T}^\top d \ln p$. Taking stock, in matrix notation, we have,

$$d \ln V = d \ln Z + (\mathbf{I} - \mathbf{T}^\top) d \ln p$$

And so,

$$\begin{aligned} d \ln \mathcal{W} &= d \ln V + (\mathbf{M} - \mathbf{I}) d \ln V \\ &= \underbrace{d \ln Z}_{\text{direct effects}} + \underbrace{(\mathbf{I} - \mathbf{T}^\top) d \ln p}_{\text{trade effects}} + \underbrace{(\mathbf{M} - \mathbf{I}) \left[d \ln Z + (\mathbf{I} - \mathbf{T}^\top) d \ln p \right]}_{\text{migration effects}} \end{aligned}$$

What remains is to solve for $d \ln p$ as a function of $d \ln Z$. Doing so requires we understand the endogeneity of population in this model.

From the logit migration probabilities, we know,

$$d \ln M_{od} = \epsilon \left(d \ln V_d - \sum_{d'} M_{od'} d \ln V_{d'} \right)$$

So we can write,

$$
\begin{aligned}
dL_{d,t} &= \sum_o M_{od,t}(d\ln M_{od})L_{o,t-1} \\
dL_{d,t} &= \epsilon \sum_o M_{od,t}\left(d\ln V_d - \sum_{d'} M_{od'} d\ln V_{d'}\right) L_{o,t-1} \\
&= \epsilon \sum_o M_{od,t}(d\ln V_d)L_{o,t-1} - \epsilon \sum_o M_{od}\left(\sum_{d'} M_{od'} d\ln V_{d'}\right) L_{o,t-1} \\
&= \epsilon(d\ln V_d)L_{d,t} - \epsilon \sum_o M_{od}\left(\sum_{d'} M_{od'} d\ln V_{d'}\right) L_{o,t-1}
\end{aligned}
$$

So then,

$$
\implies d\ln L_{d,t} = \epsilon(d\ln V_d) - \epsilon \sum_o \frac{M_{od,t}L_{o,t-1}}{\sum_o M_{od,t}L_{o,t-1}} \sum_{d'} M_{od'} d\ln V_{d'}
$$

Define $\mathbf{L}_{od,t} = \frac{M_{od,t}L_{o,t-1}}{\sum_{o'} M_{o'd,t}L_{o',t-1}}$: this is the share of persons in destination d who originated in o, so stacking, in vectors, we can write,

$$
d\ln L = \epsilon(\mathbf{I} - \mathbf{L}^\top \mathbf{M}) d\ln V
$$

Now, let's analyze prices.

We start from,

$$
p_o Y_o = \sum_d \mathbf{T}_{od} p_d Y_d
$$

We know,

$$
d\ln p_o + d\ln Y_o = \sum_d \mathbf{T}_{od}(d\ln p_d + d\ln Y_d)\frac{p_d Y_d}{p_o Y_o} + \sum_d (d\ln \mathbf{T}_{od})\mathbf{T}_{od}\frac{p_d Y_d}{p_o Y_o}
$$

Defining $\mathbf{S}_{od} = \mathbf{T}_{od}\frac{p_d Y_d}{p_o Y_o}$ which is the share of GDP in o attributed to sales in d, we can write,

$$
d\ln p_o + d\ln Y_o = \sum_d \mathbf{S}_{od}(d\ln p_d + d\ln Y_d) + \sum_d \mathbf{S}_{od}(d\ln \mathbf{T}_{od})
$$

Now,

$$d\ln \mathbf{T}_{od} = (1-\sigma)\left(d\ln p_o - \sum_{o'} \mathbf{T}_{o'd} d\ln p_{o'}\right)$$

So stacking in matrix form,

$$d\ln p + d\ln Y = \mathbf{S}(d\ln p + d\ln Y) - (\sigma-1)\left(\mathbf{I} - \mathbf{S}\mathbf{T}^\top\right) d\ln p$$

Rearranging,

$$\left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right) d\ln p = (\mathbf{S}-\mathbf{I}) d\ln Y$$

Or,

$$d\ln p = \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1} (\mathbf{S}-\mathbf{I}) d\ln Y$$

Now, note that,

$$\begin{aligned}
d\ln Y &= d\ln Z + d\ln L \\
&= d\ln Z + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M}) d\ln V \\
&= d\ln Z + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})\left[d\ln Z + (\mathbf{I} - \mathbf{T}^\top) d\ln p\right] \\
&= \left(\mathbf{I} + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})\right) d\ln Z + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})(\mathbf{I} - \mathbf{T}^\top) d\ln p
\end{aligned}$$

This means that,

$$d\ln p = \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1} (\mathbf{S}-\mathbf{I})\left[\left(\mathbf{I} + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})\right) d\ln Z + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})(\mathbf{I} - \mathbf{T}^\top) d\ln p\right]$$

Or,

$$\begin{aligned}
&\left(\mathbf{I} - \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1} (\mathbf{S}-\mathbf{I})\epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})(\mathbf{I} - \mathbf{T}^\top)\right) d\ln p \\
&\quad = \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1} (\mathbf{S}-\mathbf{I})\left(\mathbf{I} + \epsilon(\mathbf{I} - \mathbf{L}^\top\mathbf{M})\right) d\ln Z
\end{aligned}$$

Which for simplicity, we can just call, $d\ln p = \mathbf{A}^Z d\ln Z$.

This means, then, that,

$$d\ln\mathcal{W} = \left(\underbrace{\mathbf{I}}_{\text{direct effects}} + \underbrace{(\mathbf{I}-\mathbf{T}^\top)\mathbf{A}^Z}_{\text{trade effects}} + \underbrace{(\mathbf{M}-\mathbf{I})}_{\text{migration effects}} + \underbrace{(\mathbf{M}-\mathbf{I})(\mathbf{I}-\mathbf{T}^\top)\mathbf{A}^Z}_{\text{trade-migration interaction}} \right) d\ln Z$$

This allows us to separate out variance in $\mathcal{W}$ driven by direct, trade, migration, and interaction effects.

$d\ln L^0$ shocks

Now, we want to analyze,

$$d\ln\mathcal{W} = (\mathbf{I}-\mathbf{T}^\top)d\ln p + (\mathbf{M}-\mathbf{I})(\mathbf{I}-\mathbf{T}^\top)d\ln p$$

when $d\ln Z = d\ln A = 0$ but $d\ln L^0$ is allowed to vary.

Now, as $L_d = \sum_o M_{od}L_o^0$, we have that,

$$dL_d = \sum_o M_{od}(d\ln M_{od})L_o^0 + \sum_o M_{od}dL_o^0$$

We know the first term is,

$$\implies d\ln L_{d,t} = \epsilon(d\ln V_d) - \epsilon\sum_o \frac{M_{od,t}L_{o,t-1}}{\sum_o M_{od,t}L_{o,t-1}} \sum_{d'} M_{od'}d\ln V_{d'}$$

the second term can be written as,

$$\sum_o \frac{M_{od}L_o^0}{\sum_{o'} M_{o'd}L_{o'}^0} d\ln L_o^0$$

Which gives,

$$d\ln L = \epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})d\ln V + \mathbf{L}^\top d\ln L^0$$

where of course, $d\ln V = (\mathbf{I}-\mathbf{T}^\top)d\ln p$.

So, as $d\ln Z = 0$,

$$d\ln Y = \epsilon(\mathbf{I} - \mathbf{L}^\top \mathbf{M})(\mathbf{I} - \mathbf{T}^\top) d\ln p + \mathbf{L}^\top d\ln L^0$$

And we know,

$$d\ln p = \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S} - \mathbf{I}) d\ln Y$$

So,

$$\begin{aligned} d\ln p &= \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S} - \mathbf{I}) d\ln Y \\ &= \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S} - \mathbf{I}) \left[\epsilon(\mathbf{I} - \mathbf{L}^\top \mathbf{M})(\mathbf{I} - \mathbf{T}^\top) d\ln p + \mathbf{L}^\top d\ln L^0\right] \end{aligned}$$

So,

$$d\ln p = \left(\mathbf{I} - \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S} - \mathbf{I})\right)^{-1} \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S}-\mathbf{I})\mathbf{L}^\top d\ln L^0$$

B2.2 Joint shocks and the accumulation of welfare effects

Recall that,

$$d\ln L = \epsilon(\mathbf{I} - \mathbf{L}^\top \mathbf{M}) d\ln V + \mathbf{L}^\top d\ln L^0$$

and,

$$d\ln V = d\ln Z + (\mathbf{I} - \mathbf{T}^\top) d\ln p$$

and,

$$d\ln p = \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S} - \mathbf{I}) d\ln Y$$

where, $d\ln Y = d\ln Z + d\ln L$. Plugging in,

$$
\begin{aligned}
d\ln p &= \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S}-\mathbf{I})\left[d\ln Z + d\ln L\right] \\
&= \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S}-\mathbf{I})\left[d\ln Z + \epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})d\ln V + \mathbf{L}^\top d\ln L^0\right] \\
&= \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S}-\mathbf{I})\left[d\ln Z + \epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})\left[d\ln Z + (\mathbf{I}-\mathbf{T}^\top)d\ln p\right]\right. \\
&+ \mathbf{L}^\top d\ln L^0
\end{aligned}
$$

Simplifying, $\mathbf{Q} = \left(\sigma\mathbf{I} - \mathbf{S} - (\sigma-1)\mathbf{S}\mathbf{T}^\top\right)^{-1}(\mathbf{S}-\mathbf{I})$, we have,

$$
d\ln p = \mathbf{Q}\left[(\mathbf{I}+\epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M}))d\ln Z + \mathbf{L}^\top d\ln L^0 + \epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})(\mathbf{I}-\mathbf{T}^\top)d\ln p\right]
$$

So,

$$
d\ln p = (\mathbf{I} - \mathbf{Q}\epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})(\mathbf{I}-\mathbf{T}^\top))^{-1}\mathbf{Q}\left[(\mathbf{I}+\epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M}))d\ln Z + \mathbf{L}^\top d\ln L^0\right]
$$

Call,

$$
\mathbf{A}^Z \equiv (\mathbf{I} - \mathbf{Q}\epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})(\mathbf{I}-\mathbf{T}^\top))^{-1}\mathbf{Q}\left(\mathbf{I}+\epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})\right)
$$

and,

$$
\mathbf{A}^L \equiv (\mathbf{I} - \mathbf{Q}\epsilon(\mathbf{I}-\mathbf{L}^\top\mathbf{M})(\mathbf{I}-\mathbf{T}^\top))^{-1}\mathbf{Q}\mathbf{L}^\top
$$

So now,

$$
d\ln W = \underbrace{\left[(\mathbf{I} + (\mathbf{I}-\mathbf{T}^\top)\mathbf{A}^Z + (\mathbf{M}-\mathbf{I})(\mathbf{I}+(\mathbf{I}-\mathbf{T}^\top)\mathbf{A}^Z)\right]}_{\equiv\mathbf{R}^Z} d\ln Z + \underbrace{\mathbf{M}(\mathbf{I}-\mathbf{T}^\top)\mathbf{A}^L}_{\equiv\mathbf{R}^L} d\ln L
$$

So,

$$
\ln\mathcal{W}_t - \mathcal{W}_{t-1} = \mathbf{R}^Z d\ln Z_t + \mathbf{R}^L d\ln L_t^0
$$

$d\ln L$ is given as a function of the state, Z_{t-1}, as are the matrices $\mathbf{R}^Z, \mathbf{R}^L$ (mechanically,

$Z_t = Z_{t-1}\exp(d\ln Z_t)$. and $L_t = \mathbf{M}_{t-1}L_{t-1}$).

So, given $\mathcal{W}_0$,

$$\ln \mathcal{W}_t - \ln \mathcal{W}_0 \approx \sum_{n=1}^{t} d\ln W_n$$

as $d\ln \mathcal{W}_n \approx \ln \mathcal{W}_n - \ln \mathcal{W}_{n-1}$.

So then,

$$\begin{aligned}
\ln \mathcal{W}_t - \ln \mathcal{W}_0 &\approx \sum_{n=1}^{t} d\ln W_n \\
&= \sum_{n=1}^{t} \mathbf{R}_{n-1}^{Z} d\ln Z_n + \mathbf{R}_{n-1}^{L} d\ln L_n^0 \\
&= \sum_{n=1}^{t} \mathbf{R}_{n-1}^{Z} d\ln Z_n + \underbrace{\sum_{n=1}^{t} \mathbf{R}_{n-1}^{L} d\ln L_n^0}_{\text{population convergence},\equiv \mathcal{L}_t} \\
&= \sum_{n=1}^{t} \left(\mathbf{I} + \boldsymbol{\mathcal{T}}_{n-1} + \boldsymbol{\mathcal{M}}_{n-1}\right) d\ln Z_n + \mathcal{L}_t
\end{aligned}$$

where $\boldsymbol{\mathcal{T}}_{n-1}$ capture trade propagation effects for time n shocks (and because of the linearization, that matrix is measurable at time $n-1$), and $\boldsymbol{\mathcal{M}}_{n-1}$ captures migration and migration-trade interaction effects.

B2.3 Using the linearization for decomposition

For a path of shocks $d\ln Z_t^{(k)}$, we decompose the effects of each channel on welfare as, e.g.,

$$\begin{aligned}
\text{direct role}_t^{(k)} &= \frac{\sum_{n=1}^{t} d\ln Z_n^{(k)}}{\ln \mathcal{W}_t - \ln \mathcal{W}_0} \\
\text{trade role}_t^{(k)} &= \frac{\sum_{n=1}^{t} \boldsymbol{\mathcal{T}}_{n-1} d\ln Z_n^{(k)}}{\ln \mathcal{W}_t - \ln \mathcal{W}_0} \\
\text{migration role}_t^{(k)} &= \frac{\sum_{n=1}^{t} \boldsymbol{\mathcal{M}}_{n-1} d\ln Z_n^{(k)} + \mathcal{L}_t}{\ln \mathcal{W}_t - \ln \mathcal{W}_0}
\end{aligned}$$

We can also consider aggregate welfare, $\Upsilon_t = L_t^\top \mathcal{W}_t$. Decomposing any change, we have that,

$$\begin{aligned}
\Upsilon_t - \Upsilon_{t-1} &= \ln \sum_i L_{i,t}\mathcal{W}_{i,t} - \ln \sum_i L_{i,t-1}\mathcal{W}_{i,t-1} \\
\text{Törnqvist,} \quad &\approx \sum_i \frac{1}{2}(s_{it} + s_{i,t-1})(d\ln \mathcal{W}_{it} + d\ln L_{it}), \quad s_i = \frac{W_{it}L_{it}}{\Upsilon_{it}} \\
&\approx \sum_i \frac{1}{2}(s_{it} + s_{i,t-1}) \left[(\mathbf{I} + \boldsymbol{\mathcal{T}}_{t-1} + \boldsymbol{\mathcal{M}}_{t-1}) d\ln Z + \mathcal{L}_t\right]_i + \sum_i \frac{1}{2}(s_{it} + s_{i,t-1})(d\ln L_{it})
\end{aligned}$$

Now we also know $d\ln L_{it}$,

$$d\ln L_t = \epsilon(\mathbf{I} - \mathbf{L}^\top \mathbf{M}) \left[\mathbf{I} + (\mathbf{I} - \mathbf{T}^\top)\mathbf{A}^Z\right] d\ln Z_t + \mathbf{L}^\top d\ln L_{t-1}$$

Similarly, we can decompose the variance across chains (k) through,

$$\text{trade variance share}_t = \frac{\text{Var}_k\left(\sum_{n=1}^t \left(\mathbf{I} + \boldsymbol{\mathcal{T}}_{n-1}^{(k)}\right) d\ln Z_n^{(k)}\right) - \text{Var}_k\left(\sum_{n=1}^t d\ln Z_n^{(k)}\right)}{\text{Var}_k(\ln \mathcal{W}_t - \mathcal{W}_0)}$$

and similarly for migration share, and then the residual share captures are interactions and autocorrelations/covariances.

This works because, for, e.g., shock matrix Σ, we're basically attributing,

$$(I + T + M)\Sigma(I + T + M)' = \Sigma + \underbrace{T\Sigma + \Sigma T' + T\Sigma T'}_{\text{trade component}} + ...$$

And then we're accumulating the variances. All the autocorrelations from the accumulation are in the residual.

B2.4 Second order effects

Start from,

$$d\ln \mathcal{W}_o = d\ln V_o + \sum_d M_{od}(d\ln V_d - d\ln V_o)$$

Differentiating again,

$$d^2\ln \mathcal{W}_o = d^2\ln V_o + \sum_d M_{od}(d\ln M_{od})(d\ln V_d - d\ln V_o) + \sum_{od} M_{od}(d^2\ln V_d/V_o)$$

And,

$$d^2\ln V_d = d^2\ln Z_o + d^2\ln p_d - \sum_o \mathbf{T}_{od}(d\ln \mathbf{T}_{od})(d\ln p_o) - \sum_o \mathbf{T}_{od}(d^2\ln p_o)$$

But $d^2\ln Z = 0$ by construction; it's the exogenous shock. Moreover, recall,

$$d\ln \mathbf{T}_{od} = -(\sigma-1)\left(d\ln p_o - \sum_{o'} \mathbf{T}_{o'd} d\ln p_{o'}\right)$$

So,

$$d^2\ln V_d = d^2\ln p_d + (\sigma-1)\sum_o \mathbf{T}_{od}\left(d\ln p_o - \sum_{o'} \mathbf{T}_{o'd} d\ln p_{o'}\right)(d\ln p_o) - \sum_o \mathbf{T}_{od}(d^2\ln p_o)$$

Writing,

$$\mathrm{Var}_{\mathbf{T}_{\cdot d}}(d\ln p_o) = \sum_o \mathbf{T}_{od}(d\ln p_o)^2 - \left(\sum_o \mathbf{T}_{od} d\ln p_o\right)^2$$

We have,

$$d^2\ln V_d = (\sigma-1)\mathrm{Var}_{\mathbf{T}_{\cdot d}}(d\ln p_o) - \sum_o \mathbf{T}_{od}(d^2\ln p_o - d^2\ln p_d)$$

i.e., "adaptation" through trade (price variance good, as we are maximizing) and second order price effects.

Now, to recall that,

$$d\ln M_{od} = \epsilon\left(d\ln V_d - \sum_{d'} M_{od'} d\ln V_{d'}\right)$$

So,

$$d^2 \ln \mathcal{W}_o = d^2 \ln V_o + \epsilon \sum_d M_{od} \left(d \ln V_d - \sum_{d'} M_{od'} d \ln V_{d'} \right) (d \ln V_d - d \ln V_o)$$
$$+ \sum_{od} M_{od} (d^2 \ln V_d / V_o)$$

Similarly, defining,

$$\text{Var}_{\mathbf{M}_{o\cdot}} (d \ln V_d / V_o) = \sum_d \mathbf{M}_{od} (d \ln (V_d / V_o))^2 - \left(\sum_d \mathbf{M}_{od} d \ln (V_d / V_o) \right)^2$$

We can write,

$$d^2 \ln \mathcal{W}_o = d^2 \ln V_o + \epsilon \text{Var}_{\mathbf{M}_{o\cdot}} (d \ln V_d / V_o) + \sum_{od} M_{od} (d^2 \ln V_d / V_o)$$

and then filling in for $d^2 \ln V_o$,

$$d^2 \ln \mathcal{W}_o = \underbrace{(\sigma - 1) \text{Var}_{\mathbf{T}_{\cdot d}} (d \ln p_o)}_{\text{trade adaptation}} + \underbrace{\epsilon \text{Var}_{\mathbf{M}_{o\cdot}} (d \ln V_d / V_o)}_{\text{migration adaptation}} +$$
$$\underbrace{\sum_{od} M_{od} (d^2 \ln V_d / V_o) - \sum_o \mathbf{T}_{od} (d^2 \ln p_o / p_d)}_{\text{second order price effects}}$$

And note to compute these, we have that, $d \ln p = \mathbf{A}\, d \ln Z$ and $d \ln V = \left(\mathbf{I} + (\mathbf{I} - \mathbf{T}^\top) \mathbf{A} \right) d \ln Z$.

B3 Inversion

B3.1 Recovering productivity, Z_{it}

$$w_i L_i = \sum_j \left(\frac{\tau_{ij} w_i / Z_i}{P_j} \right)^{1-\sigma} w_j L_j$$

$$w_i^{\sigma} L_i Z_i^{1-\sigma} = \sum_j (\tau_{ij})^{1-\sigma} \frac{w_j L_j}{P_j^{1-\sigma}}$$

$$Z_i^{1-\sigma} = w_i^{-\sigma} L_i^{-1} \sum_j (\tau_{ij})^{1-\sigma} \frac{w_j L_j}{P_j^{1-\sigma}}$$

$$Z_i = w_i^{\frac{\sigma}{\sigma-1}} L_i^{\frac{1}{\sigma-1}} \left(\sum_j (\tau_{ij})^{1-\sigma} \frac{w_j L_j}{P_j^{1-\sigma}} \right)^{\frac{1}{1-\sigma}}$$

and,

$$P_j = \left(\sum_k \tau_{kj}^{1-\sigma} (w_k / Z_k)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

so the iteration is,

$$Z_i^{(n+1)} = w_i^{\frac{\sigma}{\sigma-1}} L_i^{\frac{1}{\sigma-1}} \left(\sum_j (\tau_{ij})^{1-\sigma} \frac{w_j L_j}{\left(\sum_k \tau_{kj}^{1-\sigma} \left(w_k / Z_k^{(n)} \right)^{1-\sigma} \right)} \right)^{\frac{1}{1-\sigma}}$$

As Z is only identified up to scale through this procedure, we impose the price in the USA to equal one, $p_{USA} = 1$ and we rescale $Z^{(n)}$ on each iteration so that $Z_{USA} = y_{USA}$ in every year.

Inverting Z requires that we have a complete panel of productivity. To form this panel and invert productivity, we interpolate GDP/cap for countries with missing values in the

WDIs. To do so, we estimate,

$$\ln y_{it} = \beta \ln pop_i + \gamma_i \cdot y_{USA,t} + \alpha_i t + \xi_i + \xi_t + e_{it}$$

and use this regression to construct GDP/cap, y_{it} for missing observations. Appendix Figure B6 shows the fit of this interpolation exercise for countries with missing time series data.

Recovering 'stationary' amenities

The migration shares equation gives us,

$$L_j = \sum_i \mu_{ij}^{-\epsilon} \left(\frac{A_j v_j}{\sum_k (\mu_{ik} A_k v_k)} \right)^{\epsilon} L_i$$

where $v_j = w_j / P_j$, which can be computed knowing the inverted Z and σ. Rearranging,

$$A_j^{-\epsilon} = L_j^{-1} \sum_i \mu_{ij}^{-\epsilon} \left(\frac{A_j v_j}{\sum_k (\mu_{ik} A_k v_k)} \right)^{\epsilon} L_i$$

which suggests the updater,

$$A_j^{(n+1)} = L_j^{1/\epsilon} \left(\sum_i \frac{\mu_{ij}^{-\epsilon} v_j^{\epsilon}}{\sum_k \mu_{ik}^{-\epsilon} \left(A_k^{(n)} v_k \right)} L_i \right)^{-1/\epsilon}$$

	(1) Trade flows	(2) Migration flows
Log distance	-0.369	-1.009
	(0.015)	(0.065)
1(Colony of origin)	0.390	1.360
	(0.050)	(0.277)
1(Colony of destination)	0.310	1.231
	(0.057)	(0.266)
1(Common colonizer)	0.479	0.227
	(0.036)	(0.438)
1(Common legal origin)	0.045	-0.076
	(0.040)	(0.402)
1(Contiguous)	0.799	1.008
	(0.027)	(0.134)
1(Common language)	0.199	1.026
	(0.018)	(0.140)
1(Same country)	1.993	2.369
	(0.134)	(0.397)
1(Same region)	0.266	-0.064
	(0.036)	(0.135)
1(Both EU)	-0.105	-0.090
	(0.028)	(0.297)
Pseudo R-squared	0.981	0.998
N obs.	716,334	225,570

Table B1: Gravity regressions of trade and migration flows on bilateral cost shifters.

	(1)	(2)	(3)	(4)	(5)
Log trade openness	−5.402			−6.346	−5.347
	(1.742)			(1.483)	(1.091)
Log GDP/cap		1.044		2.357	2.267
		(0.575)		(0.555)	(0.545)
Temperature (2019, °C)			−1.480	−1.359	−0.002
			(0.220)	(0.212)	(0.180)
Std. Dev. Warming (2080)			−25.788	−25.748	0.034
			(4.110)	(3.950)	(3.111)
Observations	174	196	186	164	164
R^2	0.061	0.016	0.345	0.479	0.397
Population weights					✓

Table B2: Determinants of the percent reduction in climate risk attributable to general equilibrium forces (trade and migration). Robust standard errors in parentheses.

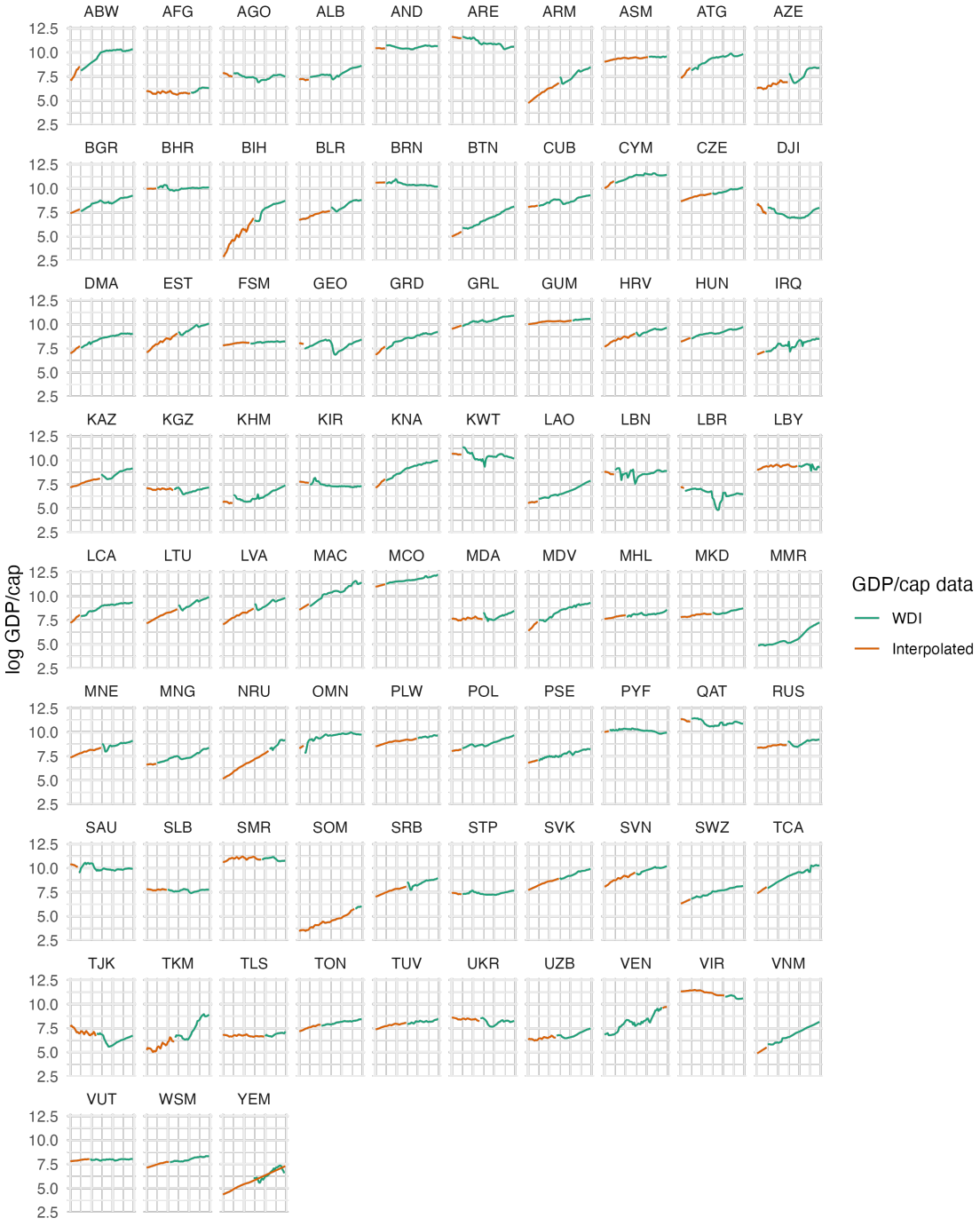


Figure B6: Interpolated and existing GDP/cap data. Time runs from 1960 to 2019.