Geography, uncertainty, and the cost of climate change

EXTREMELY PRELIMINARY: DO NOT CITE

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Abstract

This paper estimates the global welfare cost of climate change using a Spatially Integrated Assessment Model (SIAM), accounting for climatic uncertainty by integrating over different climate scenarios. SIAMs have the ability to account for adjustment mechanisms (e.g., trade and migration) to climate change. However, most work in the literature fails to account for uncertainty around the future realizations of climate. Jensen's inequality suggests that failing to integrate over the full distribution of future climate in a SIAM leads to a biased estimate of the welfare cost when the welfare function has curvature. We show theoretically that the curvature of welfare to climate depends on the strength of migration, the spatial correlation of climate shocks, and the curvature of the utility function. We then show that these second order effects are quantitatively important using simulations of a baseline model.

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1 Introduction

This paper develops a theory of how climatic uncertainty affects the economic cost of climate change in an economic geography framework, and quantifies that uncertainty using a spatial integrated assessment model (SIAM).

Global warming has the potential to impose widespread economic costs. Understanding the magnitude of those costs informs the policy response to climate change. However, estimating these costs is complex and fraught with uncertainty, particularly given the spatial and regional heterogeneity of the global economy. One approach, based on Pigouvian taxation, attempts to measure the global (or national) social cost of carbon (SCC) through a broad set of observed health and production outcomes (see, e.g., Nordhaus (2017) and Carleton and Greenstone (2022)). A different approach is to forecast the national and sub-national costs of climate change and efficacy of various policy instruments in quantitative macroeconomic frameworks (Nordhaus and Yang, 1996; Cruz and Rossi-Hansberg, 2021). Estimated costs in the latter approach tend to be lower, as macroeconomic models capture both the benefits of climate change and account for adaptation via trade, migration, and innovation.

However, the realization of future climate is uncertain; we do not know what world we will inherit tomorrow. Extant quantitative macroeconomic work on the cost of climate change fails to account for this in two ways. First, it fails to place confidence intervals around the estimates of climate change's welfare effect due to climatic uncertainty. Second, and more importantly, by failing to propagate uncertainty through the assessment model, such papers may over- or under-state the welfare impact of climate change depending on the convexity of the welfare function, due to Jensen's inequality. The convexity of the welfare function governs the economic costs associated with tail risk phenomenon, i.e, catastrophic events that occur with non-zero probability (Weitzman, 2009; Weitzman, 2011). In fact, the inability of standard SIAMs to allow for these tail risks into their welfare assessment is seen as a significant failure of these models (Pindyck, 2013).

A common missing feature through this profile of work is the lack of a proper framework that can deal with uncertainty in future climate scenarios. Uncertainty in climate projections is driven by three components: scenario uncertainty, internal variability, and intermodel uncertainty (Schwarzwald and Lenssen, 2022). This paper emphasizes the third form of uncertainty: in particular, we focus on the equilibrium climate sensitivity

(ECS) estimates across CMIP5 (Coupled Model Intercomparison Project) and CMIP6 models from Schlund et al. (2020). ECS estimates forecast the change in average global temperature in the long-run after a doubling of atmospheric CO2. The focus of this paper is to estimate the welfare cost associated with this doubling. Barnett et al. (2022) highlights how important uncertainty in our knowledge of future climate scenarios (and other features) is towards how we think of welfare costs, and appropriate policy design. While this paper does not compute optimal policy, we use Monte Carlo simulations as provide a feasible way of accounting for uncertain climate scenarios in estimating welfare losses, though we emphasize we are not the first to use Monte Carlo methods in a spatial setting (Dingel and Tintelnot, 2021).

Our goal is to estimate the size of the confidence intervals around mean estimates of economic damages associated with climate change, and to measure the bias in that estimate from failing to properly integrate over the distribution of future climate shocks. The paper begins with a theoretical decomposition of what dictates the curvature of the welfare function in a broad class of spatial models. This allows for a framework to analyze the different economic forces that uncertainty matter for welfare loss estimation. We use a general spatial model to characterize the second-order impacts of a shock to geographic fundamentals, which govern how climatic uncertainty affects welfare. We show that the curvature of the welfare function depends on the migration response to climate, and how spatial linkages through trade can amplify the cost of spatially autocorrelated shocks. In the second part of the paper, we present an economic model that features these key economic forces and use it to evaluate the welfare costs of climate change across different regions. The model eliminates some of the sophisticated elements of other SIAMs to isolate the forces we argue are key, and buys us the computational ability to integrate over a large number of climate scenarios.

Our starting point for the model is Allen and Arkolakis (2014). The model allows for climate to affect exogenous region-specific amenities and productivities, while allowing agents in the model to make optimal decisions pertaining to where they want to live and what they consume. In short, the model features spatially heterogeneous effects of climate change on model primatives, and includes adaptation mechanism via trade and migration. We abstract from dynamic impacts of climate change through altering the global growth trajectory, natality decisions, and the endogenous production of emissions. We instead take the path of climate as given and use the model to measure the forces which govern the convexity of the welfare function. Our goal is to characterize the importance of climatic uncertainty in economic geography models rather than use the model to conduct policy analysis. Pindyck (2013) makes the point that IAMs are particularly ill-suited to be able to conduct welfare or policy analysis from climate change. One of the key reasons for this, he argues, is the inability to account for tail risk events. We provide a methodology wherein we can incorporate these events easily.

Our work compliments the burgeoning literature which uses SIAMs to study and forecast the economic effects of climate change. Cruz and Rossi-Hansberg (2021) use a sophisticated dynamic spatial model to determine welfare losses in a laissez-faire (no policy) world as a result of global warming. They show that welfare losses are concentrated in the global south, and also assess the impact of abatement technologies, carbon taxes, and clean energy subsidies. Krusell and Smith Jr (2022) also build a dynamic model with heterogeneous regions and endogenous consumption-savings decisions, without any trade or migration, to compute welfare effects of climate change. Rudik et al. (2021) and Cruz (2023) account for sectoral heterogeneity in a similar model, while Nath (2021) evaluates the impact of climate change on sectoral reallocation due to nonhomothetic preferences. Conte (2022) develops a spatial model to understand the role of trade networks, migration costs, and agricultural yields to quantify how real output and migration in Sub-Saharan Africa is impacted as a result of global warming. Balboni (2019) uses a spatial model to understand the impact of sea level rises on coastal cities, and quantifies the cost of road investments in Vietnamese coastal regions.

The rest of this paper is organised as follows. Section 2 presents a theoretical decomposition of welfare in spatial models, and explains what might drive convexity in the welfare function. Section 3 presents our quantitative model that is used for welfare analysis. Section 4 describes the model calibration, damage function estimation, and the distribution of future climate. Section 5 shows our preliminary results. Section 6 concludes and offers next steps.

2 Theory

Economic assessment models map changes in climate C, a random variable, to welfare via a function $\mathcal{W}$ whose value for a given $C = c$ is determined through the general equilibrium of an economic model. Formally, $\mathcal{W} : c \mapsto \mathbb{R}^+$. The welfare change (in percent terms) associated with a particular climate scenario is $\mathcal{W}(c)/\mathcal{W}(0)$ where $c = 0$ represents some baseline. However, climate forecasts are uncertain and thus

$\text{Var}(C) > 0$. Assessment models that do not account for this uncertainty report $\mathcal{W}(\mathbb{E}_C[C])$ as the welfare cost of climate change. This is not the true forecast, $\mathbb{E}_C[\mathcal{W}(C)]$ when $\mathcal{W}$ has curvature. This is due to Jensen's inequality, which states,

$$\mathbb{E}_C[\mathcal{W}(C)] \neq \mathcal{W}(\mathbb{E}_C[C]) \quad \text{if} \quad \frac{d^2\mathcal{W}}{dc^2} \neq 0.$$

In particular, using a second-order Maclaurin expansion,

$$\mathbb{E}_C[\mathcal{W}(C)]/\mathcal{W}(0) - \mathcal{W}(\mathbb{E}_C[C])/\mathcal{W}(0) = \frac{1}{2}\frac{d^2\mathcal{W}}{dc^2}\frac{1}{\mathcal{W}}\bigg|_{c=0} \times \text{Var}(C) + \mathcal{O}(C^3). \tag{1}$$

Equation (1) shows that the curvature of the welfare function determines the importance of accounting for uncertainty. The importance of higher moments – e.g., the skewness C, which may embed tail scenarios of 6°C of warming or more – is reflected in higher-order derivatives of the welfare function. Our goal is to understand how variability in climate affects our understanding of welfare, and so our theoretical analysis abstracts from the economic forces that make the skewness and fat-tailed nature of the distribution of future temperature relevant for welfare analysis, though our quantitative framework can assess these impacts, too.

A simple model of welfare We begin by presenting a simple and general spatial model to derive the forces that give curvature to the welfare function. In the model, there is a continuum of individuals of measure one that decide where to live across N sites indexed by i. In each location, they receive indirect utility u_i which depends on the number of individuals already living in the location, ℓ_i, and economic activity elsewhere, as summarized by local real income, $M_i(c, \{\ell_j\})$ which captures the entire supply side of the economy, including interactions across space, like trade. Climate c directly enters utility, and also affects production and thus M_i. Geography enters the model through both factor mobility (the ability for agents to move across sites) and spatial linkages (embodied in M_i). Utilitarian welfare in the model is then summarized by,

$$\mathcal{W} = \sum_i \ell_i u_i(c, M_i).$$

A spatial equilibrium is an allocation $\{\ell_i\}_{i=1}^N$ such that:

1. there is no spatial arbitrage: workers are indifferent across locations, so $u_i = u_j \; \forall i, j$ (in particular, at

the spatial equilibrium, $u_i = \mathcal{W}$ by construction), and,

2. the labor market clears: all workers are allocated to some location, $\sum_i \ell_i = 1$

Climate affects welfare through three channels: (1) the direct effect on utility via amenities $\frac{\partial u_i}{\partial c}$ (2) via production and therefore real income, $\frac{dM_i}{dc}$, and (3) through affecting the spatial distribution of economic activity $\frac{d\ell_i}{dc}$. We restrict our analysis to efficient allocations so there are no welfare gains simply from altering the allocation of factors in the economy. We moreover restrict our analysis to cases in which, $\frac{\partial \log u_i}{\partial \log M_i} = 1$.

This assumption is consistent with a utility function that is linear in real income, as in the common Cobb-Douglas case. That is, we rule out nonhomotheticities, though these may be important (Nath, 2021). Our framework allows us to set an Engel elasticity to any constant in $(0, 1]$, but we choose 1 for simplicity. This assumption does not meaningfully alter the analysis but eliminates a parameter that makes our resulting derivation appear more opaque. Setting constant and location-invariant elasticities is common in the spatial literature. Under these assumptions, a shock in climate affects welfare to the first order via the expression,

$$\frac{d\mathcal{W}}{dc} = \mathbb{E}\left[\frac{\partial u_i}{\partial c}\right] - \mathcal{W} \cdot \mathbb{E}\left[\frac{d \log M_i}{dc}\right], \tag{2}$$

where expectations weight by ℓ_i. Using equation (2), the constant elasticity assumption, and the equilibrium conditions, the second order effect is given by,

$$\frac{d^2 \log \mathcal{W}}{dc^2}\frac{1}{\mathcal{W}} = \underbrace{\mathbb{E}\left[\frac{d^2 u_i}{dc^2}\right]}_{\text{curvature of utility}} + \underbrace{\text{Cov}\left(\frac{d \log \ell_i}{dc}, \frac{\partial \log u_i}{\partial c} + \frac{d \log M_i}{dc}\right)}_{\text{adaptation via migration}} \tag{3}$$

$$- \underbrace{\text{Var}\left(\frac{d \log M_i}{dc}\right)}_{\text{spatial inequality}} + \underbrace{\text{Cov}\left(\frac{\partial \log u_i}{\partial c}, \frac{d \log M_i}{dc}\right)}_{\text{Correlation of damages}}, \tag{4}$$

See Appendix A.1 for a derivation.

Discussion What equation (4) informs us is that the convexity of the welfare function comes from the convexity of utility, alongside two economic geography forces. Regardless of the underlying utility function, whose convexity is unknown and can be altered by monotonic transforms of the utility function without affecting agents choices, these economic geography forces convexify (or make concave) the welfare function.

First, there is the sorting of people across locations, given by the covariance term. As an agent's location is the result of a utility-maximizing choice, agents will sort towards improving locations ($\partial u_i/\partial c > 0$) or away from locations where M_i falls in response to climate. That sorting generates convexity is illustrated in Figure 1: under the assumption that utility is linear in climate, without migration, welfare responds linearly. However, the ability of agents to migrate to improving regions, and away from ones experiencing welfare losses necessarily means that the welfare curve must lie above the line.

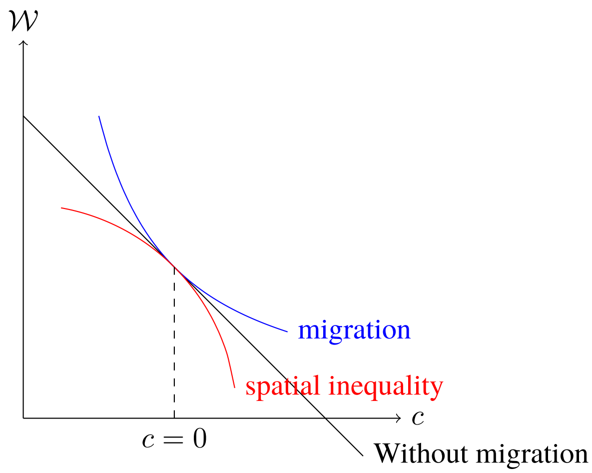

Figure 1: Welfare as a function of climate when indirect utility is linear in climate. Agents' ability to adapt through migration generates a convex welfare function, but spatial inequality bends it concave.

The third term in the second order expansion of the welfare function is the amplification of the production response to climate. An simple example makes this point transparent. Assume, as we will do in the quantitative section, that the production side of the economy is Armington: each region produces a unique traded good that are aggregated with a CES aggregator, and suppose trade costs are iceberg. Real income can be written as w_i/P_i, where w_i are local wages, and P_i is a CES ideal price index that takes on a market access form. Consider a partial equilibrium (i.e., hold w_i fixed) shock to climate. Under this assumption, the variance in $\log M_i$ is simply the variance in P_i. Shocks to the price index can be decomposed as,

$$\frac{\partial \log P_i}{\partial c} \propto \sum_j \underbrace{\left(\frac{\tau_{ij} z_j}{P_i}\right)^{-\sigma}}_{\text{trade shares, } \equiv X_{ij}} \frac{d \log z_j}{dc}$$

where z_j is the marginal cost of production in location j, and τ_{ij} are the iceberg trade costs, and both enter with raised to the power of the trade elasticity. Suppose that the marginal cost shocks are distributed with mean 0, variance 1 and covariances ρ_{ij}. Spatial correlation occurs when $\text{Cov}(\tau_{ij}, \rho_{ij}) > 0$; i.e., when the shock correlation structure mimics the pattern of trade (which depends on geography), and nearby shocks are correlated. Then,

$$\text{Var}\left(\frac{d\log P_i}{dc}\right) = 1 + \sum_j X_{ij}(\tau_{ij})^2 + \underbrace{\sum_j \sum_i X_{ij}(\tau_{ij})^2 \rho_{ij}}_{\text{spatial correlation}}.$$

What the above formula reveals is that the variance of P_i in a broad class of models increases as spatial correlation increases, a point made in Dingel, Meng, et al. (2022).

The last term is negative by the logic of spatial equilibrium – changes in amenities must be offset by changes in prices. Differentiating $u_i = \mathcal{W}$, we see that,

$$\frac{\partial \log u_i}{\partial c} + \frac{\partial \log u_i}{\partial \log M_i}\frac{d\log M_i}{dc} = \frac{d\log \mathcal{W}}{dc}.$$

Using our assumption on the elasticity of agents' Engel curves, we can write the last term as,

$$\text{Cov}\left(\frac{\partial \log u_i}{\partial c}, \frac{d\log M_i}{dc}\right) = \text{Cov}\left(\frac{\partial \log u_i}{\partial c}, \frac{d\log \mathcal{W}}{dc} - \frac{\partial \log u_i}{\partial c}\right) = -\text{Var}\left(\frac{\partial \log u_i}{\partial c}\right)$$

which captures the spatial heterogeneity in the amenity response to climate change. The more varied, the more concave.

Returning to equation (4), whether the migration term or the shock term dominate is an empirical question. The welfare function can either be more concave or convex than the utility function due to these economic geographic forces. These changes in shape dictate whether we under- or over-estimate welfare losses in spatial models by failing to account for uncertainty. In Section 5, we empirically derive the shape of the welfare function using the calibration of the model presented in Section 3.

3 Quantitative Model

This section describes our model that is used to undertake welfare analysis from climate shocks. The model is a version of that of Allen and Arkolakis (2014), adapted to highlight the role of climate, trade, migration, and the concavity of utility.

Environment The world is comprised of a discrete set of regions indexed by i or j. Regions are characterized by both their location in space alongside their fundamental amenity value $\bar{A}_i$ and labor productivity $\bar{Z}_i$, both of which are a function of temperature T_i. Each location produces a unique consumption variety with a linear-in-labor technology, which is traded around the world subject to iceberg trade costs $\tau_{ij} \in [1, \infty)$. A unit mass of freely mobile agents choose where to locate amongst these locations and how much to consume.

Preferences Utility for agent ω is as follows,

$$u_i(\omega) = \nu_i(\omega) A_i C_i$$

Where $\nu_i(\omega)$ is Fréchet distributed with location parameter 1 and scale parameter θ. Location-specific amenities are given by A_i and are a product of fundamental amenities and the climate such that:

$$A_i = \bar{A}_i F_A(T_i) \tag{5}$$

C_i is consumption utility of a CES aggregator across all varieties,

$$C_i = \left(\sum_j c_{ji}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where c_{ji} denotes the amount of the consumption good an agent in i sources from location j.

Agents inelastically supply one unit of labor labor and earn reward w_i, which is their income. Indirect utility can therefore be written as,

$$v_i(\omega) = \nu_i(\omega) A_i(T_i)(w_i/P_i)$$

where P_i is the price index associated with the consumption aggregator. Due to the Fréchet shocks, the share of the population ℓ_i in location i is given by,

$$\ell_i = \frac{(A_i(w_i/P_i))^\theta}{\sum_j (A_j(w_j/P_j))^\theta}.$$

Technology Each location makes a single variety and sells it in a competitive global market with linear technology,

$$q_i = Z_i \ell_i$$

where $Z_i = \bar{Z}_i F_Z(T_i)$ represents productivity as a product of fundamental productivity and the impact of climate. Producers act competitively, so the price of a good produced in i and sold in j reflects the iceberg trade cost τ_{ij} times the marginal cost, or out-of-the-gate price,

$$p_{ij} = \tau_{ij} \frac{w_i}{Z_i}.$$

Thus the CES price index faced by consumers in destination j is,

$$P_j = \left(\sum_i \left(\tau_{ij} \frac{w_i}{Z_i} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

Equilibrium Equilibrium is a set of wages w_i such that when households and firms take them as given and behave optimally, the goods market clears, which occurs when income is equal to the value of all goods sold,

$$w_i \ell_i = \sum_j p_{ij} c_{ij}.$$

A vector of unique wages exists up to scale for this according to the theorems of Allen and Arkolakis (2014), as this model is isomorphic in its positive predictions (equilibrium prices and quantities) to one in which there is free mobility, and local amenities respond endogenously to population with $d \log B_i / d \log \ell_i = -\frac{1}{\theta}$, though our model does not feature endogenous amenities entering the welfare calculation. A complete treatment of the model equilibrium can be found in Appendix A.3.

Welfare Our welfare function is inclusive of the expected value of the Fréchet shocks and is thus

$$\mathcal{W} = \left(\sum_i \left(A_i (w_i / P_i) \right)^{\theta} \right)^{1/\theta}.$$

Our decomposition in Section 2 applies to this economy despite the idiosyncratic variation in utility from the Fréchet shocks and our ex-ante notion of expected utility in place of the welfare function defined previously. We show this formally in Appendix A.2.

4 Calibration

We invert the model presented in Section 3. Inversion simply means rationalizing the observed w_i and ℓ_i as an equilibrium of the model for a fixed set of A_i and Z_i terms, alongside elasticities ξ, σ, and θ. The inversion is unique due to the theorems of Allen and Arkolakis (2014).

Data Data on population and GDP for $1^\circ \times 1^\circ$ cell levels comes from the G-Econ 4.0 project (Nordhaus, 2006). We use data for the years 1990, 1995, 2000, and 2005, and invert the model in each year to form a panel of A_{it} and Z_{it}. We interpret differences across years in fundamentals as driven by climate, and we use this variation to identify our damage functions. Gridded temperature data comes from Berkeley Earth Surface Temperature (BEST). This dataset provides data as frequent as daily maximum, minimum and average temperature at a granular spatial level. We use the database that provides annual average temperature at a resolution of $1^\circ \times 1^\circ$.

Parameterization Our model has three key parameters: θ, which governs the migration response to shocks; σ, the Armington trade elasticity, the role of spatially autocorrelated shocks; and ξ, which governs the elasticity of utility to real income. We take these parameters as given from the literature. We set $\sigma = 3.8$, following the meta-analysis of estimated Armington trade elasticities in Bajzik et al. (2020). Following Havraneka et al. (2015), we set $\xi = 0.5$. We set $\theta = 1.25$. Our choice is motivated by the isomorphism in Allen and Arkolakis (2014) that a model with local congestion $\tilde{\lambda}$ and idiosyncratic Frechet preference dispersion $\tilde{\theta}$ is equivalent to one with local congestion $\lambda = \tilde{\lambda} - 1/\tilde{\theta}$ and free mobility. Following Cruz and Rossi-Hansberg (2021), if $\tilde{\lambda} = -0.3$ and $\tilde{\theta} = 2$, then we need to pick our θ such that $-\frac{1}{\theta} = -0.3 - 0.5$. We take the trade cost matrix $\{\tau_{ij}\}$ from Desmet et al. (2018). Table A1 gives a full description of the model parameters and their sources.

Inversion outcomes We plot the recovered temperature-adjusted amenities ($\bar{A}_i$) and productivities ($\bar{Z}_i$) from inverting the model using 2005 G-Econ data in Figure 2. We detail the inversion procedure in Appendix B.1. The model rationalizes low population regions like Northern Canada, Siberia, the Amazon rain forest, alongside deserts like the Saharan, Gobi, and Tibetan plateau as having low amenity value. Populous areas like western Europe, eastern China, and the northeastern United States appear high-amenity as well. However, as a spatial equilibrium framework, the model rationalizes high-population areas with low real wages as high-

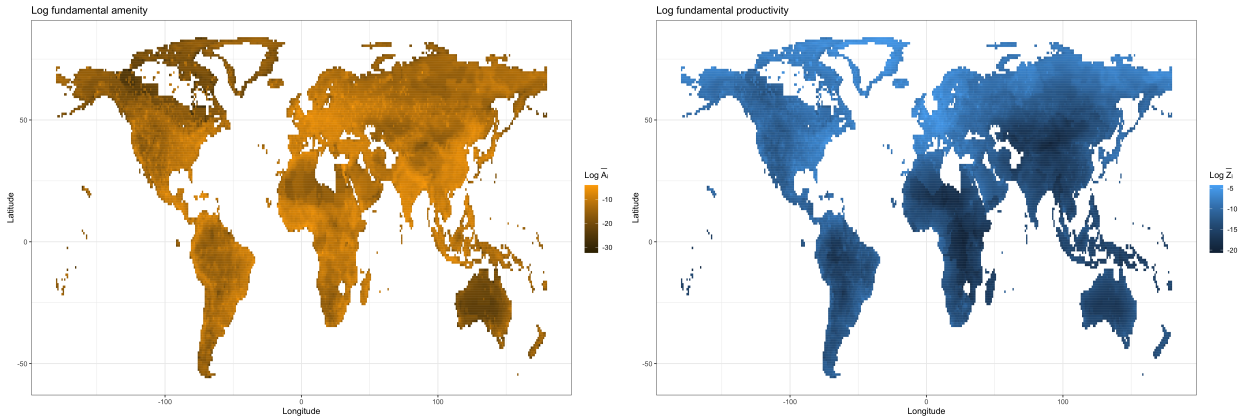

Figure 2: Recovered fundamentals from the model inversion in 2005, adjusted for 2005 local temperature using the estimated damage functions. Left: log amenities, $\log \bar{A}_i$. Right: log productivities, $\log \bar{Z}_i$. The inversion identifies these parameters only up to scale, rendering the interpretation of the levels meaningless.

amenity value too, like those in West Africa. In terms of productivity, the east coast of the United States, alongside western Europe, Eastern China, alongside urban Brazil, Japan, and Australia all appear high productivity while Central Asia, Amazonia, and vast swaths of sub-Saharan Africa do not. In short, the inversion procedure produces sensible fundamentals.

Damage functions We parameterize the relationship between temperature and fundamentals as,

$$X_{it} = S_t \bar{X}_i F_X(T_{it})$$

where $X_{it} = \{A_{it}, Z_{it}\}$ are the inverted productivities and amenities for each year. Our inversion procedure only identifies these parameters up to scale, S_t. Taking logs and rearranging, we form the estimating equation,

$$\log X_{it} = \log F_X(T_{it}) + \chi_i + \chi_t + u_{it}, \tag{6}$$

where χ_i and χ_t are cell and year fixed effects, and u_{it} represents error from model mispecification, as other unobserved shocks may influence X_{it}. We follow Cruz and Rossi-Hansberg (2021) and estimate $F_X(T_{it})$ by approximating the function with,

$$\log F_X(T_{it}) = \sum_k \beta_k T_{it} \times 1(T_{it} \in \mathcal{T}_k)$$

where $\mathcal{T}_k$ are ventiles of the temperature distribution. As β_k estimates the average derivative of $\log F(T_{it})$

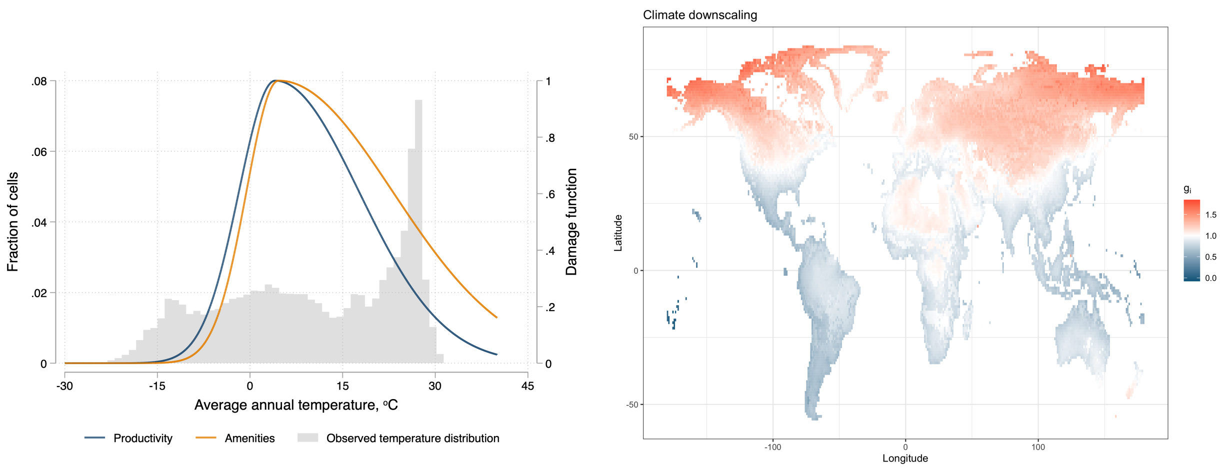

Figure 3: Left: Damage functions and distribution of cell-level annual temperature, 1990-2005. Right: Estimated downscaling parameters $\hat{g}_i$.

along the distribution T_{it}, we numerically integrate our resulting β_ks and use nonlinear least squares to fit a parametric form on $F(T_{it})$,

$$F(T_{it}) = \exp(-\gamma_1(T_{it} - T^*)^2) \times 1(T_{it} < T^*) + \exp(-\gamma_2(T_{it} - T^*)^2) \times 1(T_{it} \geq T^*)$$

i.e., bell-shaped damage functions on $(0, 1)$ that peak at T^* and have slopes on either side controled by γ_1 and γ_2, which are allowed to vary. Our functional form assumption for $F_X(T)$ captures the fact that fundamentals peak around certain temperature values, a point made in Burke et al. (2015).

For consistent nonparametric estimates of γ_1, γ_2 and T^* for each set of fundamentals, we require $\log F_X(T_{it}) \perp u_{it} \mid \chi_i, \chi_t$, which rules out concerns that our estimates may be biased as high-productivity places may be in high-temperature areas due to unobserved confounders, or that shocks to temperature and productivity may both be trending secularly. However, we are not immune to the criticism that the spectrum of unmeasured climate shocks (e.g., drought) may be correlated with temperature. Finally, in practice, we do not include region fixed effects because our panel is very short ($t = 1, ..., 4$). Thus, we parameterize χ_i as a function of cell-level covariates: a second-order polynomial in latitude and longitude, and geographic covariates from the G-Econ database, including log distance to coast, terrain roughness, and so on; see Appendix B.1 for details.

Estimating equation (6) provides estimates of peak productivity and amenities around 10°C, similar to Burke et al. (2015)'s estimate of around 13°C. Figure 3 plots the damage functions and the distribution of cell-level temperature. As some cells are to the left and right of the peaks of the damage functions, global warming will benefit some regions, and worsen others.

Temperature downscaling To integrate model outcomes of the distribution of global temperature, we need to fix the mapping from global to local temperature in order to propagate uncertainty in global temperatures through the model. Following Mitchell (2003) and Cruz and Rossi-Hansberg (2021), we assume and estimate a linear relationship between changes in global temperature and changes in local temperature,

$$t_{it} = g_i T_t + \alpha_i + \varepsilon_{it} \tag{7}$$

where the location-specific coefficient g_i tells us how much temperature of a region, t_{it}, changes as global temperature, T_t, changes by $1°C$. The key object of interest here is g_i which we parameterize as a second-order polynomial in observable like latitude, longitude, and geographic covariates as we do when estimating equation (6). To estimate equation (7), we use the entirety of the Berkeley temperature dataset, from the first year in which there is global annual coverage, 1894. In Figure 3, we display the map of estimated down-scaling coefficients. Our estimates account for 41% of the changes in local temperature changes from cell level fixed effects (α_i) over the sample period. Locations for which the slope on global temperature, g_i exceeds 1 (and thus warm faster than the average cell) are broadly located in the global north, and Sahara, while cells that warm slower than the global average are located in the in the global south. The estimation procedure recovers few cells – mostly small pacific islands – for which $\hat{g}_i < 0$, implying that these locations cool as global temperature rises, perhaps reflecting changing trade winds or sea level rise.

Equilibrium climate sensitivity distribution We take the distribution of equilibrium climate sensitivity across the 70 participating models in CMIP (Coupled Model Intercomparison Project) 5 and 6 from Schlund et al. (2020). With these ECS estimates, we fit a log-normal distribution via maximum likelihood to recover the distribution of ECS across the range of potential warming scenarios. In Appendix Figure A1, we plot the estimated density function. Our procedure results in a ECS distribution that roughly corresponds to that estimated in Sherwood et al. (2020) using more sophisticated methods.

5 Welfare

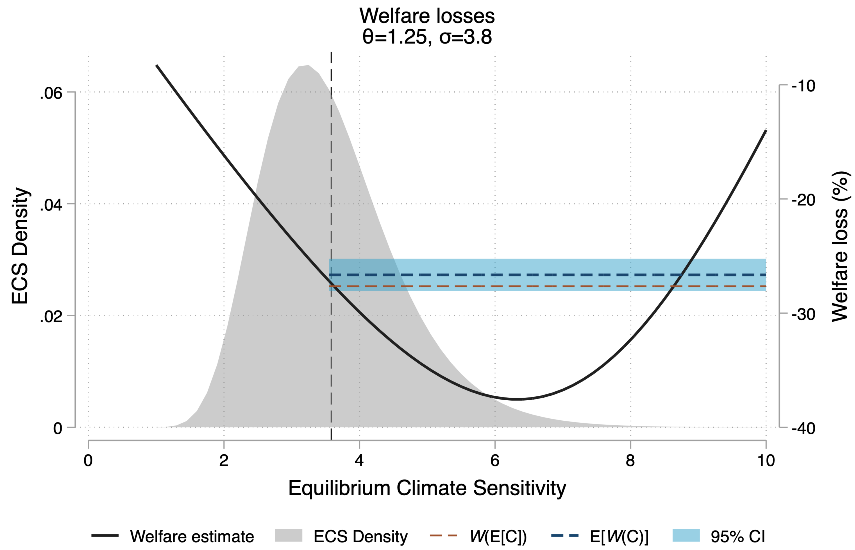

Figure 4: Welfare as a function of global climate, and the estimated cross-model ECS distribution.

We estimate the model over the ECS distribution to get Monte Carlo estimate of $\mathbb{E}[W(C)]$. We proceed as follows. First, we discretize the cross-model ECS distribution into 60 different potential global temperature values. For each global temperature rise, we obtain the implied downscaling. We then transform the downcaling into a scaling of $\bar{A}_i$ and $\bar{Z}_i$ using the estimated damage functions. We estimate the model using these new fundamentals to compute welfare.

The welfare function, as represented as welfare *loss* with respect to the baseline $1 - W(C)/W(0)$ is plotted in Figure 4. The loss is concave, due to adaptive forces, suggesting that the naive estimated loss using $\mathcal{W}(\mathbb{E}[C]) \approx 26.7\%$ is higher than the Monte Carlo estimate (using $\mathbb{E}[\mathcal{W}(C)]$) of 27.6%. Moreover, the associated 95% confidence intervals are fairly tight around $\mathbb{E}[\mathcal{W}(C)]$, ranging from 25.2% to 29.1% welfare loss, and containing the "linear" estimate. Our estimated welfare loss bends backwards at high degrees of warming as the marginal damage in some locations is outweighed by gains elsewhere at high degrees of warming. Our results suggest that adaptation is enough to reverse the potential for catastrophic losses at high degrees of warming.

These welfare numbers for the welfare cost of a doubling of atmospheric carbon are high, but that is because they are not discounted, and it may take up to a century for higher temperatures to be realized. Applying a discount factor to the welfare loss of 0.985 over 100 years suggests welfare losses on the order of 6%, in line with the existing literature.

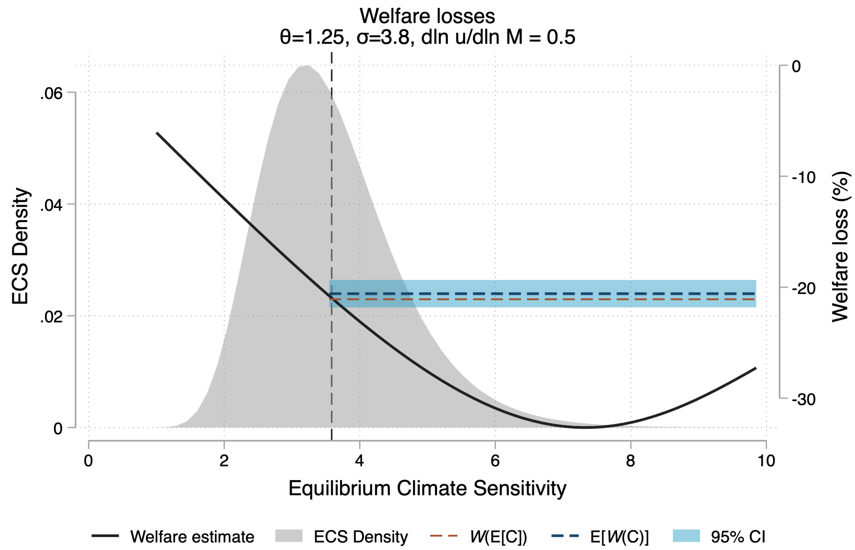

Figure 5: Welfare as a function of global climate, and the estimated cross-model ECS distribution.

In Figure 5, we set $\frac{d \log u_i}{d \log M_i} = 1/2$ so that utility is more concave in income. This lowers the losses by several percentage points (a level shift) but dampens the curvature (a flattening) yet it does not change the overall pattern – welfare loss is concave and bends back; peak damages occur between 6-8°C of warming.

Local uncertainty so far, the only uncertainty in the model comes from global temperatures, but the mapping from global to local temperature is also uncertain. To study the role of local uncertainty in shaping welfare, we fix global temperature at 3.6 degrees of warming, and allow g_i to vary.

We estimate the local distribution of the temperature downscaling, g_i via a Bootstrap procedure. First, we take our estimates of $g_i = X_i' \hat{\beta}$, where X_i contains a polynomial in local physical characteristics, and generate a distribution of $\beta^{(n)}$ (where n indexes the nth Bootstrap sample) by drawing $\beta^{(n)} \sim N(\hat{\beta}, \hat{V})$, where N is a normal distribution and $\hat{V}$ is the estimated variance-covariance matrix from the OLS regression (allowing for two-way clustering with cells and years). We then generate a bootstrap $g_i^{(n)} = X_i' \beta^{(n)}$, and simulate the counterfactual using this downscaling.

We plot variance of $g_i^{(n)}$ across bootstrap samples against the baseline g_i, and map it in Figure 6. What it shows is that we are more uncertain (i.e., there is more variance across bootstrap samples) of the local downscaling in places that the downscaling is greater. These areas are predominately located in Northern Canada and Siberia.

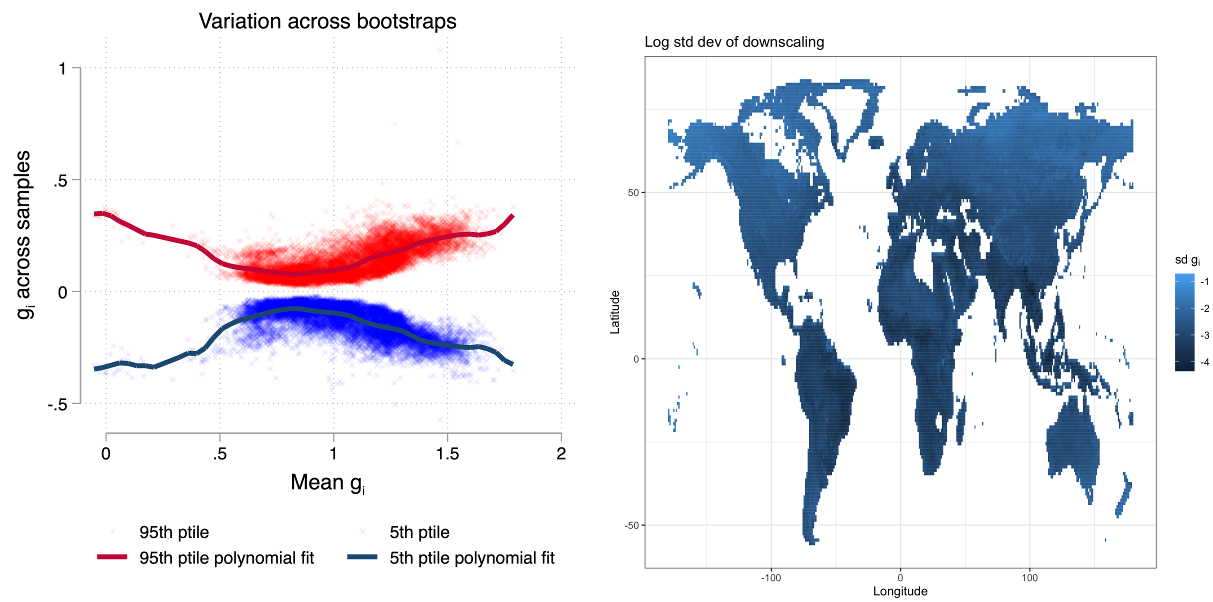

Figure 6: Left: 5th and 95th percentiles (net the mean) of the distribution of sampled g_i vs. $\bar{g}_i$. Right $\log sd(g_i)$ across space.

In Figure 7, we compute the mean of welfare over the bootstrap samples. It has a thin but longer right tail (less loss) but with most mass concentrated around the mean such that again $\mathbb{E}[\mathcal{W}(C)]$ does not differ significantly from the naive $\mathcal{W}(\mathbb{E}[C])$.

6 Conclusion and future steps

The primary objective of this paper is to provide both a theoretical description and quantification of the economic forces that shape how climatic uncertainty affects forecasts of the welfare impacts of climate change in a broad class of quantitative spatial models.

We show it is the second-order impacts of climate on welfare that determine the importance of climatic variability on welfare. The size of these second order effects depend on not only the concavity of the utility function (which is unknown) but also how migration and trade affect welfare. Migration, as an adaptive mechanism, convexifies the welfare function, while trade amplifies the welfare loss of spatially correlated

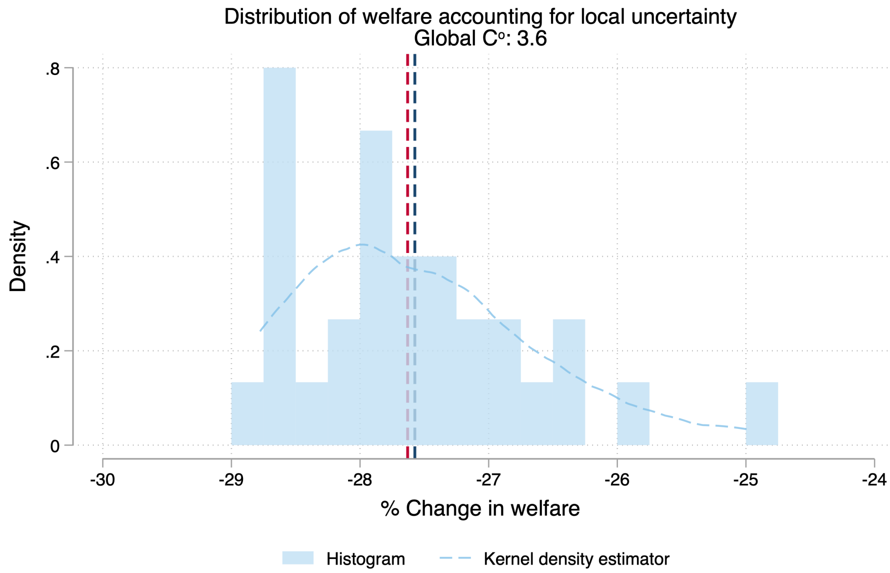

Figure 7: Distribution of % change in welfare over the bootstrap samples. Sample mean in blue, welfare of the mean of the sample in red.

shocks and bend it concave.

Our quantitative model marries computational feasibility with these key spatial forces that drive heterogeneous responses across regions: trade and migration. This paper shows that second order effects are quantitatively significant, as the our estimated welfare loss is concave, suggesting that baseline models may overstate the welfare loss from climate chance, and is robust to changing the curvature of utility to income.

Future iterations of this paper will study more sources of climatic uncertainty in terms of a richer understanding of the local realization of climate, and estimate richer damage functions that map additional climate moments (e.g., local annual temperature variance) to damages on economic fundamentals.

This paper is the first in a long class of SIAMs that is able to integrate climactic uncertainty in its framework without compromising on the rich spatial heterogeneity in the global economy. However, inevitably, our model is unable to capture certain effects that might be of interest when thinking about future uncertainty. This include adding dynamics, or adding a feedback mechanism from the climate into the economy itself. This would enable the model to integrate uncertainty when thinking about optimal policy design. Our hope is that this project highlights a way to deal with climactic uncertainty in a feasible manner, since this is critical in informing the welfare costs imposed by global warming.

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A Theory appendix

A.1 Derivation of the second-order decomposition with free mobility

First,

$$\mathcal{W} = \sum_i \ell_i u_i(c, \underbrace{M_i}_{\equiv w_i/P_i})$$

assumptions:

- $\frac{\partial^2 \log u_i}{\partial c \partial M_i} = 0$ separability of income and amenities
- $\frac{d \log u_i}{d \log M_i} = 1$ or any constant; log-linear Engel curves
- $u_i = \mathcal{W}$ spatial equilibrium
- $\sum_i \ell_i = 1$ inelastic aggregate labor supply

First,

$$\frac{d\mathcal{W}}{dc} = \sum_i \ell_i \frac{\partial u_i}{\partial c} + \mathcal{W} \sum_i \ell_i \frac{d \log M_i}{dc}$$

Apply D_c to the first term

$$\sum_i \frac{d\ell}{dc} \frac{\partial u_i}{\partial c} + \sum_i \ell_i \left(\frac{\partial^2 u_i}{\partial c} + \frac{\partial^2 u_i}{\partial c \partial M_i} \frac{dM_i}{dc} \right)$$

Note that under assumption (1),

$$\frac{\partial^2 u_i}{\partial c \partial M_i} = \frac{1}{u_i} \frac{\partial u_i}{\partial c} \frac{\partial u_i}{\partial M_i}$$

Differentiating $\mathcal{W}$ again it is convenient to write it as,

$$\frac{d\mathcal{W}}{dc} = \mathcal{W} \left[\sum_i \ell_i \frac{\partial \log u_i}{\partial c} + \sum_i \ell_i \frac{d \log M_i}{dc} \right]$$

and then the last term is,

$$\sum_i \frac{d\ell_i}{dc} \frac{d \log M_i}{dc} - \sum_i \ell_i \left(\frac{d \log M_i}{dc} \right)^2 + \sum_i \ell_i \frac{1}{M_i} \frac{d^2 M_i}{dc}$$

So putting it all together,

$$\begin{aligned}
\frac{d^2\mathcal{W}}{dc^2} = &\sum_i \frac{d\ell}{dc} \frac{\partial u_i}{\partial c} + \sum_i \ell_i \left(\frac{\partial^2 u_i}{\partial c} + \frac{1}{u_i} \frac{\partial u_i}{\partial c} \frac{\partial u_i}{\partial M_i} \frac{dM_i}{dc} \right) \\
&+ \mathcal{W} \left[\sum_i \ell_i \frac{\partial \log u_i}{\partial c} + \sum_i \ell_i \frac{d \log M_i}{dc} \right] \sum_i \ell_i \frac{d \log M_i}{dc} \\
&+ \mathcal{W} \left[\sum_i \frac{d\ell_i}{dc} \frac{d \log M_i}{dc} - \sum_i \ell_i \left(\frac{d \log M_i}{dc} \right)^2 + \sum_i \ell_i \frac{1}{M_i} \frac{d^2 M_i}{dc} \right]
\end{aligned}$$

Do more elasticity-formats and rearranging,

$$\begin{aligned}\frac{d^2\mathcal{W}}{dc^2}\frac{1}{\mathcal{W}} &= \sum_i \ell_i \frac{d\log \ell_i}{dc}\frac{\partial \log u_i}{\partial c} + \sum_i \ell_i \left(\frac{\partial^2 u_i}{\partial c}\frac{1}{u_i} + \frac{1}{(u_i)^2}\frac{\partial u_i}{\partial c}\frac{\partial u_i}{\partial M_i}\frac{dM_i}{dc}\right) \\ &+ \left[\sum_i \ell_i \frac{\partial \log u_i}{\partial c} + \sum_i \ell_i \frac{d\log M_i}{dc}\right]\sum_i \ell_i \frac{d\log M_i}{dc} \\ &+ \left[\sum_i \frac{d\ell_i}{dc}\frac{d\log M_i}{dc} - \sum_i \ell_i \left(\frac{d\log M_i}{dc}\right)^2 + \sum_i \ell_i \frac{1}{M_i}\frac{d^2 M_i}{dc}\right]\end{aligned}$$

and again,

$$\begin{aligned}\frac{d^2\mathcal{W}}{dc^2}\frac{1}{\mathcal{W}} &= \sum_i \ell_i \frac{d\log \ell_i}{dc}\frac{\partial \log u_i}{\partial c} + \sum_i \ell_i \left(\frac{\partial^2 u_i}{\partial c}\frac{1}{u_i} + \frac{\partial \log u_i}{\partial c}\frac{\partial \log u_i}{\partial \log M_i}\frac{d\log M_i}{dc}\right) \\ &+ \left(\sum_i \ell_i \frac{\partial \log u_i}{\partial c}\right)\left(\sum_i \ell_i \frac{d\log M_i}{dc}\right) + \left(\sum_i \ell_i \frac{d\log M_i}{dc}\right)^2 \\ &+ \left[\sum_i \frac{d\ell_i}{dc}\frac{d\log M_i}{dc} - \sum_i \ell_i \left(\frac{d\log M_i}{dc}\right)^2 + \sum_i \ell_i \frac{1}{M_i}\frac{d^2 M_i}{dc}\right]\end{aligned}$$

Rearranging,

$$\begin{aligned}\frac{d^2\mathcal{W}}{dc^2}\frac{1}{\mathcal{W}} &= \text{cov}(\frac{d\log \ell_i}{dc}, \frac{\partial \log u_i}{\partial c}) + \mathbb{E}[\frac{\partial^2 u_i}{\partial c}\frac{1}{u_i}] + \text{cov}(\frac{d\log u_i}{dc}, \frac{d\log M_i}{dc}) - \text{var}(\frac{d\log M_i}{dc}) \\ &+ \text{cov}(\frac{d\log \ell_i}{dc}, \frac{d\log M_i}{dc}) + \mathbb{E}[\frac{1}{M_i}\frac{d^2 M_i}{dc}] + 2\mathbb{E}[\frac{d\log u_i}{dc}]\mathbb{E}[\frac{d\log M_i}{dc}]\end{aligned}$$

now we employ the fact that,

$$\frac{d^2 y}{dx^2} = \frac{d^2 \log y}{dx^2} + \left(\frac{d\log y}{dx}\right)^2$$

to rewrite the terms,

$$\mathbb{E}[\frac{\partial^2 u_i}{\partial c}\frac{1}{u_i}] = \mathbb{E}[\frac{1}{M_i}\frac{d^2 M_i}{dc}] + 2\mathbb{E}[\frac{d\log u_i}{dc}]\mathbb{E}[\frac{d\log M_i}{dc}]$$

into,

$$\mathbb{E}[\frac{\partial^2 \log u_i}{\partial c^2}] + \mathbb{E}[\frac{d^2 \log M_i}{dc^2}] + \left(\mathbb{E}[\frac{\partial \log u_i}{\partial c}] + \mathbb{E}[\frac{d\log M_i}{dc}]\right)^2 = \underbrace{\mathbb{E}[\frac{\partial^2 \log u_i}{\partial c^2}] + \mathbb{E}[\frac{d^2 \log M_i}{dc^2}]}_{\equiv \mathcal{C}(u_i)} + \left(\frac{d\mathcal{W}}{dc}\frac{1}{\mathcal{W}}\right)^2$$

So, finally,

$$\begin{aligned}\frac{d^2\mathcal{W}}{dc^2}\frac{1}{\mathcal{W}} &= \mathcal{C}(u_i) + \text{cov}(\frac{d\log \ell_i}{dc}, \frac{\partial \log u_i}{\partial c}) + \text{cov}(\frac{d\log u_i}{dc}, \frac{d\log M_i}{dc}) - \text{var}(\frac{d\log M_i}{dc}) \\ &+ \text{cov}(\frac{d\log \ell_i}{dc}, \frac{d\log M_i}{dc}) + \left(\frac{d\mathcal{W}}{dc}\frac{1}{\mathcal{W}}\right)^2\end{aligned}$$

A.2 Welfare with Fréchet shocks

If agents recieve idiosyncratic location specific preference shocks, the literature generally assumes the idiosyncratic taste draws follow a Fréchet distribution (with shape parameter θ and scale parameter 1). In this case, welfare can be expressed as:

$$\mathcal{W} = \left(\sum_i v_i(\ell_i, P_i, c)^\theta \right)^{\frac{1}{\theta}}$$

We can show that the previous derivations of first and second order effects of climate on welfare can go through in this case as well. To begin, consider the distribution of workers ℓ_i in a location which is given by:

$$\begin{aligned} \ell_i &= \frac{v_i^\theta}{\sum_j v_j^\theta} \\ &= \left(\frac{v_i}{\mathcal{W}} \right)^\theta \end{aligned}$$

Now, consider a climate shock whose first order effect can be expressed as:

$$\begin{aligned} \frac{\mathrm{d}\mathcal{W}}{\mathrm{d}c} &= \mathcal{W}^{1-\theta} \left[\sum_i v_i^{\theta-1} \frac{\partial v_i}{\partial c} + \sum_i v_i^{\theta-1} \frac{\partial v_i}{\partial \ell_i} \frac{\mathrm{d}\ell_i}{\mathrm{d}c} + \sum_i v_i^{\theta-1} \frac{\partial v_i}{\partial P_i} \frac{\mathrm{d}P_i}{\mathrm{d}c} \right] \\ &= \mathcal{W} \left[\sum_i \frac{1}{\mathcal{W}^\theta} v_i^{\theta-1} \frac{\partial v_i}{\partial c} + \sum_i \frac{1}{\mathcal{W}^\theta} v_i^{\theta-1} \frac{\partial v_i}{\partial \ell_i} \frac{\mathrm{d}\ell_i}{\mathrm{d}c} + \sum_i \frac{1}{\mathcal{W}^\theta} v_i^{\theta-1} \frac{\partial v_i}{\partial P_i} \frac{\mathrm{d}P_i}{\mathrm{d}c} \right] \\ &= \mathcal{W} \left[\sum_i \ell_i \frac{\partial v_i / v_i}{\partial c} + \sum_i \ell_i \frac{\partial v_i / v_i}{\partial \ell_i} \frac{\mathrm{d}\ell_i}{\mathrm{d}c} + \sum_i \ell_i \frac{\partial v_i / v_i}{\partial P_i} \frac{\mathrm{d}P_i}{\mathrm{d}c} \right] \qquad \text{since } \ell_i = \left(\frac{v_i}{\mathcal{W}} \right)^\theta \\ &= \mathcal{W} \left[\sum_i \ell_i \frac{\partial v_i / v_i}{\partial c} + \sum_i \alpha \frac{\mathrm{d}\ell_i}{\mathrm{d}c} + \sum_i \ell_i \frac{\partial v_i / v_i}{\partial P_i} \frac{\mathrm{d}P_i}{\mathrm{d}c} \frac{P_i}{P_i} \right. \\ &= \mathcal{W} \left[\sum_i \ell_i \frac{\partial \ln v_i}{\partial c} + \beta \sum_i \ell_i \frac{\mathrm{d} \ln P_i}{\mathrm{d}c} \right] \end{aligned}$$

which carries the same interpretation as shown in the simpler case. We can obtain a similar second order decomposition here as well.

A.3 Quantitative Model Equilibrium

First, we define the revenue of firms in i from selling to region j as:

$$X_{ij} = p_{ij} c_{ij} = \left(\frac{p_{ij}}{P_i} \right)^{1-\sigma} C_i \tag{8}$$

Markets are said to clear if income is equal to the value of goods sold in all locations, i.e:

$$
\begin{aligned}
w_j \ell_j &= \sum_i X_{ij} \quad \forall j \in I \\
\rightarrow w_j \ell_j &= \sum_i \left(\frac{p_{ij}}{P_i} \right)^{1-\sigma} C_i
\end{aligned} \tag{9}
$$

Further, we require aggregate labor markets to clear such that:

$$
\sum_i \ell_i = 1 \tag{10}
$$

Spatial Equilibrium: Given a set of parameters $\{\theta, \sigma, \xi\}$ and trading costs τ_{ij}, a spatial equilibrium is a distribution of workers $\{L_i\}$, quantities $\{Q_i, C_i, c_{ij}\}$, and prices $\{P_i, p_{ij}, w_i\}$ such that:

1. Markets clear as in (9)
2. Aggregate labor markets clear as in (10)
3. Workers make optimal decisions about where to live, highlighted by (3)
4. Workers make optimal consumption decisions
5. Local price indices are given by (3)

B Inversion

B.1 Inversion

The goal of the inversion is to rationalize observed w_i, ℓ_i, τ_{ij} as an equilibrium of the model given parameters σ, ξ, θ. 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.

Recovering productivity We invert productivities using goods market clearing. In particular, we start with,

$$w_i \ell_i = \sum_j p_{ij} c_{ij}$$

This can be rewritten as,

$$w_i \ell_i = \sum_j p_{ij} \left(\frac{p_{ij}}{P_j} \right)^{-\sigma} \frac{w_j}{P_j} L_j$$

Simplifying further,

$$w_i \ell_i = \sum_j \frac{\left(\tau_{ij} \frac{w_i}{Z_i} \right)^{1-\sigma}}{\left(\sum_k \left(\tau_{kj} \frac{w_k}{A_k} \right)^{1-\sigma} \right)} w_j \ell_j$$

Which can be written as,

$$Z_i = w_i^{\frac{\sigma}{\sigma-1}} \ell_i^{\frac{1}{\sigma-1}} \left(\sum_j \frac{(\tau_{ij})^{1-\sigma}}{\left(\sum_k \left(\tau_{kj} \frac{w_k}{Z_k} \right)^{1-\sigma} \right)} w_j \ell_j \right)^{\frac{1}{1-\sigma}},$$

which is a fixed point equation in A_i. We use this form iterations,

$$Z_i^{(n+1)} = w_i^{\frac{\sigma}{\sigma-1}} \ell_i^{\frac{1}{\sigma-1}} \left(\sum_j \frac{(\tau_{ij})^{1-\sigma}}{\left(\sum_k \left(\tau_{kj} \frac{w_k}{Z_k^{(n)}} \right)^{1-\sigma} \right)} w_j \ell_j \right)^{\frac{1}{1-\sigma}}$$

and $Z_i^{(n)} \to Z_i$.

Recovering amenities

The population equation,

$$\ell_i \propto \left(A_i (w_i / P_i)^{\xi} \right)^{\theta}$$

allows us to recover the A_is up to arbitrary scale, provided we construct the P_i terms using the recovered productivities.

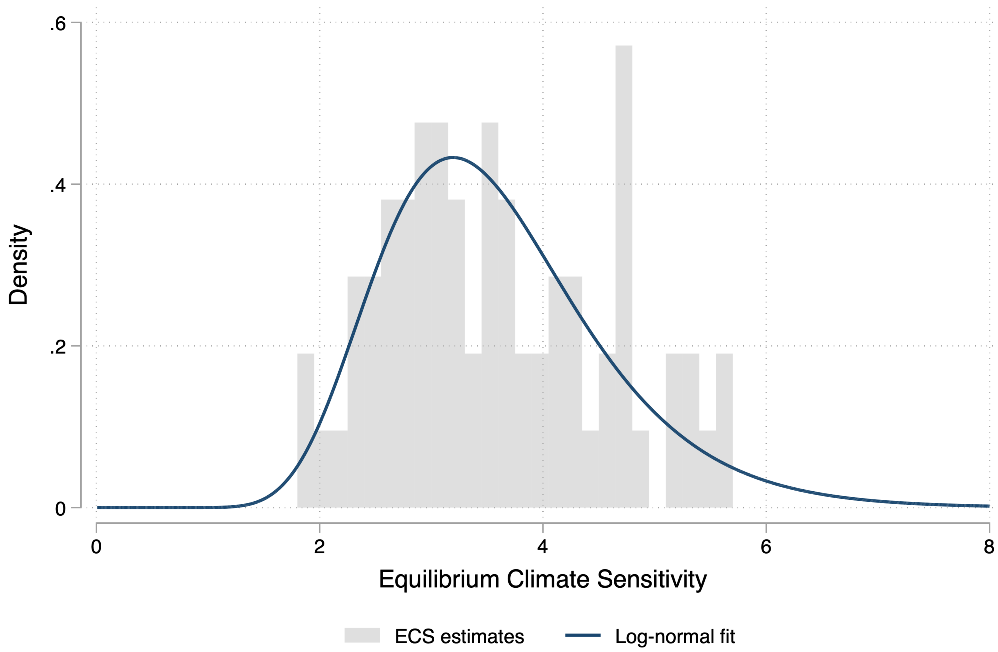

Figure A1: Estimated ECS distribution across CMIP5 and CMIP6 models.

B.2 Calibration

Parameter	Value	Description	Source
ξ	0.5	Concavity of utility	Havraneka et al. (2015)
σ	3.8	Armington trade elasticity	Bajzik et al. (2020)
$\tilde{\theta}$	2	Migration elasticity	Cruz and Rossi-Hansberg (2021)
$\tilde{\lambda}$	-0.3	Congestion elasticity	Desmet et al. (2018)
θ	1.25	Fréchet dispersion	$-(\tilde{\lambda} - 1/\tilde{\theta})^{-1}$

Table A1: Model parameters and their sources