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Climate Change Economics over Time and Space

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Abstract

With average temperature ranging from −20°C at the North Pole to 30°C at the Equator and with global warming expected to reach 1.4°C to 4.5°C by the year 2100, it is clear that climate change will have vastly different effects across the globe. Given the abundance of land in northern latitudes, if population and economic activity could freely move across space, the economic cost of global warming would be greatly reduced. However, spatial frictions are real: migrants face barriers, trade and transportation are costly, physical infrastructure is not footloose, and knowledge embedded in clusters of economic activity diffuses only imperfectly. Thus, the economic cost of climate change is intimately connected to these spatial frictions. Building on earlier integrated assessment models (IAMs) that largely ignored space, in the past decade there has been significant progress in developing dynamic spatial integrated assessment models (S-IAMs) aimed at providing a more realistic evaluation of the economic cost of climate change, both locally and globally. This review discusses this progress and provides a guide for future work in this area.

1. INTRODUCTION

The average annual temperature ranges from around −20°C at the North Pole to around 30°C at the Equator (**Figure 1**). This baseline temperature range of 50°C is much larger than the expected warming of the Earth due to anthropogenic climate change: Depending on future emissions, the Intergovernmental Panel on Climate Change (IPCC) estimates that by 2100, global surface temperature will increase by 1.4°C to 4.5°C compared to preindustrial levels (IPCC 2021). Therefore, while climate change will be very costly at equatorial latitudes, where it is already very hot, it will have more benign effects at polar latitudes, where temperatures today are too cold to foster large concentrations of people and economic activity. Therefore, climate change is a spatial phenomenon.

If some regions are bound to fare worse and others are likely to fare better, could reshuffling population and economic activity across space mitigate the impact of global warming? One constraint might be land availability. However, according to the spatially disaggregated data set G-Econ 4.0 (see **https://gecon.yale.edu/**), 91% of world GDP in 2005 was produced on only 10% of the world's land, inhabited by 75% of the global population (Desmet & Rossi-Hansberg 2015). With much empty land still available, particularly at northern latitudes, there might be scope for relocating economic activity to regions that are less vulnerable to climate change.

Yet, moving is costly. In addition to political barriers, there are many other costs associated with migrating. If moving people is difficult, another way of locally adapting is to shift production to sectors that are hit less hard by global warming. However, changing local specialization is only possible if there is trade, which allows people to produce a different basket of goods from the one they consume. Of course, trade is costly, too. In addition to migration and trade costs, there are other frictions to moving economic activity across space. If coastal cities become permanently inundated because of rising oceans, or particular areas get hit by storms, the physical infrastructure and the local knowledge embedded in these economic clusters are lost, and it takes time and additional investments for new clusters to emerge elsewhere. The bottom line is that the variety

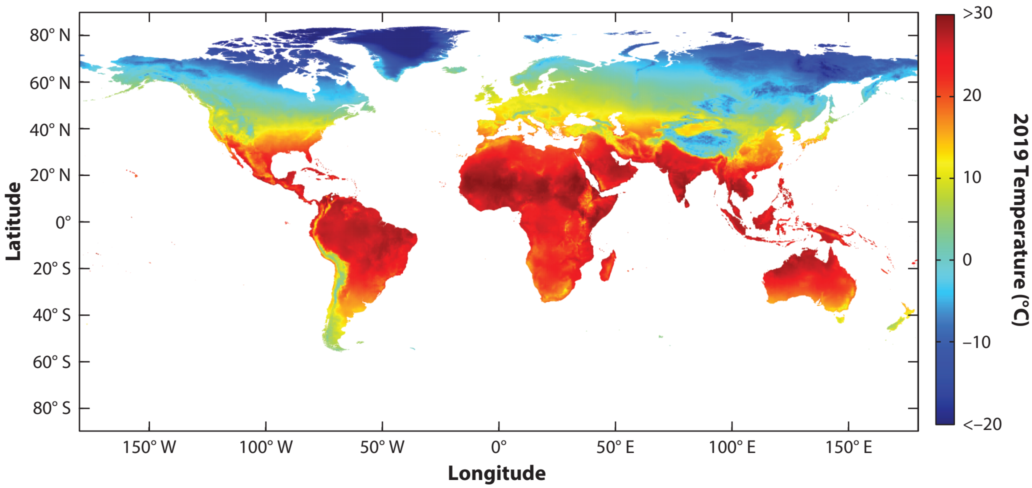

Figure 1

Temperature (°C) in 2019. Data from Climatic Research Unit gridded Time Series (CRU TS) v4, aggregated from monthly to annual via simple average.

of spatial frictions to move goods, people, capital, technology, and any other factor of production should be central to evaluating the economic impact of global warming.

There is solid evidence documenting both the spatial heterogeneity in the impact of climate change and the role of moving as an adaptation mechanism to rising temperatures.[1] The reduced-form evidence shows a nonlinear relationship between temperature and output, suggesting that many places will lose from global warming, but some will gain (Burke et al. 2015b, Hsiang et al. 2017). Micro studies have also described the heterogeneous vulnerability of different sectors to climate change (Schlenker & Roberts 2009, Zhang et al. 2018). The impact of climate change on migration has been documented both in historical contexts and in today's world (D'Andrea et al. 2011, Feng et al. 2011). In studies on the impact of global warming on different sectors, changing specialization patterns and trade have been shown to be significant (Rosenzweig & Parry 1994).

While a vast number of reduced-form empirical studies have documented many key facts about the economic impact of global warming across space, we need structural models to evaluate the economic cost of climate change, decompose the most relevant economic channels, and think about policy solutions. One reason is that reduced-form evidence is limited to the impact of climate change until now. Statistically extrapolating into new economic configurations that we have not yet observed is problematic, especially given the long time horizons. To make appropriate predictions, we need models that combine everything we know about the workings of the world economy and its relation to climate. Another reason is that reduced-form evidence typically cannot isolate particular adaptive responses, nor can it account for how these responses depend on policy incentives or characteristics of the local economy. We need models to generate counterfactuals that help us assess the impact of policy and the importance of spatial frictions in determining the cost of climate change.

Ideally, these climate assessment models should be global, have high spatial resolution, and be dynamic. A global approach is needed, because all local emissions mix rapidly in the atmosphere to generate changes in global temperatures, which in turn affect local temperatures. That is, carbon emissions are a global externality. The model should also have a high spatial resolution to accommodate both the large spatial heterogeneity in damages and the possibility of adaptation by moving economic activity across regions. Finally, the model should be dynamic, since most of the impact of today's emissions will be experienced in the future. In recent decades, Nordhaus (1993) and others have pioneered the use of integrated assessment models (IAMs) that combine standard economic models with the main insights of climate science to evaluate the economic impact of global warming. While some of these models focus on more than one region (Nordhaus 2008, 2010), they lack the necessary geographic resolution to quantify the role of spatial frictions in migration, investments, trade, and innovation. What we need, instead, are dynamic spatial integrated assessment models (S-IAMs) that follow some of the structure of traditional IAMs but allow for high spatial resolution and account for the appropriate interaction between locations as well as for local and aggregate growth through technological innovation or capital accumulation.

In the past decade, there has been significant progress in developing S-IAMs. The construction of these models has been aided by the burgeoning literature on quantitative spatial economics (for a review, see Redding & Rossi-Hansberg 2017). This literature has progressively produced more realistic and detailed models that incorporate empirically well-grounded spatial relationships. Desmet & Rossi-Hansberg (2015) provide an early S-IAM that explores the role of migration and trade in a one-dimensional model that focuses on global warming across latitudes. High-resolution models that allow for both latitude and longitude, and thus more realistic geography,

[1]For a general discussion of the role of adaptation to climate change, readers are referred to the recent book by Kahn (2021).

include those by Desmet et al. (2021), who evaluate the cost of coastal flooding; Conte et al. (2021), who analyze the role of trade as an adaptation mechanism; and Cruz & Rossi-Hansberg (2024), who propose a novel method of estimating structural damage functions that incorporate the impact of global warming on natality as well as fundamental amenities and productivity levels. Although these frameworks are dynamic, the forward-looking decisions of agents are simplified into a sequence of static decisions in order to keep the models computationally tractable. Complementary to this approach is the one by Krusell & Smith (2022), who use a high-resolution model with forward-looking investment and savings but without trade and migration. Other S-IAMs have been applied to study a variety of issues: Nath (2020), Conte (2023), and Cruz (2023) focus on the relationship between global warming, structural change, and development; Burzyński et al. (2022) study the impact of climate change on high-skilled and low-skilled migration; Balboni (2021) analyzes flooding and infrastructure investment in Vietnam; Rudik et al. (2022) emphasize the role of labor reallocation and trade in the US context; and Bilal & Rossi-Hansberg (2023) study the role of anticipation and adaptation to extreme weather events in the United States in a model that incorporates both forward-looking migration and capital investments.

In this article, we aim to survey this recent literature. In Section 2, we discuss the reduced-form empirical evidence on the spatial impact of global warming and on the spatial responses to climate change. Our goal is to show that the spatial dimension of climate change is readily observable in the data and hence is a first-order issue when evaluating the impact of global warming. We do not intend to be comprehensive in our review of the reduced-form literature, but rather to motivate the spatial approach in studying climate change. Section 3 sketches the main elements of a standard S-IAM. We start with a discussion of the desired elements of S-IAMs and then delve into the core structures that have been used until now. Section 4 discusses how these models are quantified, paying particular attention to the estimation of structural damage functions. Section 5 presents some of the key findings of these models, and it shows how results would change if we did not incorporate a high spatial resolution in climate-related damages. Section 6 explores several applications of S-IAMs, with a focus on different adaptation mechanisms and policies. Section 7 discusses some of the open questions in this research area and concludes.

2. REDUCED-FORM EVIDENCE ON THE SPATIAL IMPACT OF CLIMATE CHANGE

The impact of climate change is heterogeneous across space, for at least four reasons. First, global warming is not occurring at the same rate everywhere. Over the past 50 years, equatorial latitudes have on average experienced slower warming than more northern latitudes. Even within latitudes, there is quite a bit of variation. **Figure 2** depicts the fitted linear trend change in local temperatures between 1970 and 2019. As can be seen, some regions in Alaska, northern Europe, and Siberia have witnessed temperature changes exceeding 3°C, while other regions closer to the equator have experienced negligible changes.[2] The spatial heterogeneity in local warming is large.

Second, the Earth has a baseline temperature range of 50°C, so global warming is bound to have a very different impact at equatorial latitudes, where it is already very hot, and at more northern latitudes, where it is much colder. Many studies described below show this heterogeneity in

[2]To construct **Figure 2**, we estimate a linear trend for every 0.5° × 0.5° cell in the world between 1970 and 2019 and plot the change in the fitted values during this period. This avoids distortions coming from idiosyncratic changes at the beginning and end of the sample. Simple differences in temperature between 1970 and 2019 exhibit a similar pattern. For ease of visualization, we limit the axis to represent only values in the 2nd to 98th percentile of temperature changes. The largest changes, close to the North Pole, are larger than 5°C.

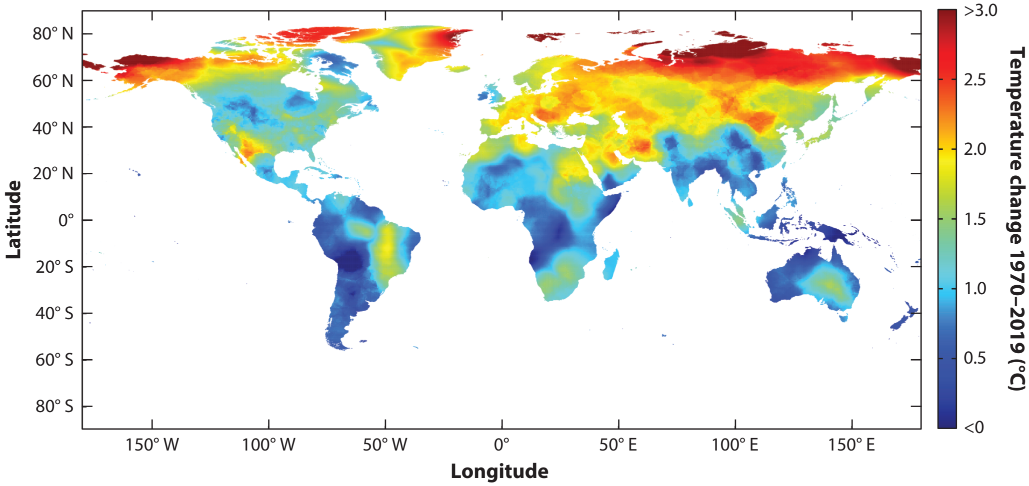

Figure 2

Temperature change (°C), 1970–2019. Average change is 1.51°C. Data from Climatic Research Unit gridded Time Series (CRU TS) v4, aggregated from monthly to annual via simple average.

damages from higher temperatures. Cold areas, in most studies, are found to gain from higher temperatures, while warm regions tend to lose significantly.

Third, heterogeneity in sectoral specialization makes some locations more vulnerable to global warming than others. Agriculture is more sensitive to temperature than manufacturing or services. This implies that agricultural regions in already warm locations tend to be hit particularly hard by climate change, whereas agricultural regions in colder locations may enjoy rising crop yields.

Fourth, beyond temperature and specialization, a location's geography also determines its vulnerability to the different effects of global warming. Miami and Mumbai are prone to coastal flooding due to rising sea levels, whereas Moscow and Madrid are not. In addition to coastal flooding, changes in the frequency of extreme weather events, such as storms and hurricanes, also vary across the world's geography.

We now discuss some of the reduced-form empirical evidence on the spatial impact of climate change that motivates and supports these four claims. We also explore the reduced-form evidence on spatial adaptation responses. This body of work demonstrates, we believe, that these spatial dimensions of climate change are evident in the data.

2.1. The Measured Effect of Temperature on Output and Productivity

There is extensive reduced-form evidence on the heterogeneous effect of temperature changes across locations. Dell et al. (2014) provide a detailed early survey of the literature that investigates the relationship between temperature and output. As documented by Burke et al. (2015b) in a study of 166 countries for the period 1960–2000, this relationship is nonlinear. They find an optimal temperature of 13°C, with locations above this level losing output when temperature increases and locations below this threshold gaining output. Hsiang et al. (2017) also identify heterogeneous effects in the context of US counties, with many counties losing and some benefiting from increases in temperatures.

The evidence on whether the impact depends on a location's level of development is more mixed. On the one hand, Burke et al. (2015b) find no difference in the estimated nonlinear relationship between temperature and output when comparing poor and rich countries. According to their study, the only reason poor countries fare worse is because they are already hot to start with. On the other hand, using panel data at the country level, Dell et al. (2012) find that higher temperatures reduce growth only in poor countries. They estimate that a 1°C increase in temperature in less developed countries lowers growth by 1.3 percentage points. Whether we would expect temperature to affect the growth of output, rather than its level, is another point of contention. Recent work by Nath et al. (2023) concludes that higher temperatures do not affect long-run growth rates, but only the long-run level of GDP per capita.[3]

Some of the measured heterogeneous effects on output are the result of differences in local sectoral specialization. Namely, different locations produce in different industries, and industries are differentially impacted by climate change. At the sectoral level, most attention has been paid to agriculture. Using US data, Schlenker & Roberts (2009) find that crop yields for corn, soybeans, and cotton increase with temperature up to around 30°C, after which they sharply decline. Though less sensitive to temperature, productivity in other sectors has also been found to depend on temperature. Using a panel of Indian manufacturing firms, Somanathan et al. (2021) estimate that output declines by 2% for each 1°C increase in temperature. In the case of Chinese manufacturing plants, Zhang et al. (2018) show that productivity declines by 0.56% on days with temperatures exceeding 32°C. In recent work, Cruz (2023) estimates the nonlinear effect of temperature on value added in six different sectors. Using a panel from 1950 to 2017 for a large set of countries, he concludes that agriculture and construction are the most climate-sensitive sectors. He finds that a temperature increase of 1°C increases agricultural productivity by 3% in the coldest countries but lowers it by 6% in the hottest countries. Trade and transportation are also sensitive to climate, but less so, whereas industry displays nonsignificant responses to warming. The nonlinear effect of temperature in different sectors, together with sectoral specialization, implies that the overall impact of climate change differs across space.

One issue with this evidence is that it often confounds the direct impact of temperature on productivity with adaptive responses. As such, these findings can be used as target moments to quantify structural models, but not as fixed relationships to make predictions. The Lucas critique applies! There are many dimensions of adaptation that can affect these reduced-form relations. Adaptation in agriculture has received particular interest. Using data on six staple crops for the entire world, Hultgren et al. (2022) estimate that adaptive responses could halve global losses from climate change by the end of the twenty-first century. Analyzing corn yields in the United States, Burke & Emerick (2016) find that long-run adaptation has mitigated less than half of the short-run effects of extreme heat exposure. Focusing on specific adaptation mechanisms, Jagnani et al. (2021) show that Kenyan farmers respond to higher temperatures early in the growing season by using more pesticides and less fertilizer.

Another adaptive response consists in moving away from vulnerable locations. In fact, some of the human migrations of the past have been driven by changes in climatic conditions. The archaeological record of settlement and abandonment of the Saqqaq, Dorset, and Norse cultures in Greenland, for example, coincides with abrupt temperature changes in the past 4,500 years (D'Andrea et al. 2011). A more recent example is the Dust Bowl in the 1930s, which drove 2.5 million Americans from the Great Plains to California (Hornbeck 2012). Focusing on the present period, changes in crop yields in Mexico have been shown to increase the rate of emigration to the United States. Specifically, a 10% drop in crop yields is estimated to increase migration by 2% (Feng et al. 2011). Similarly, asylum applications to the European Union are also sensitive to climate shocks in source countries. The increase is nonlinear, implying that future warming

[3]Other relevant studies are by Wilson (2019) and Bilal & Rossi-Hansberg (2023), who estimate the heterogeneous effects of extreme weather events across counties in the United States.

is likely to lead to an acceleration in climate refugees (Missirian & Schlenker 2017). Adaptation through migration is, of course, endogenous to border frictions and migration costs. Hence, the ability to migrate will affect the reduced-form estimates of the impact of temperature on output, wages, and population.

Adaptation can also occur by shifting specialization, a process facilitated by trade. According to Fagan (2009), during the Medieval Warm Period, England was exporting wine to France, and vineyards were found as far north as in southern Norway. Costinot et al. (2016) explore how reallocating crops and changing trade patterns mitigate the negative impact of climate change on agriculture. Rosenzweig & Parry (1994) estimate the effect on the world food supply when allowing for both local adaptation and trade. To understand the scope of trade as an adaptation mechanism, Dingel et al. (2019) show that it may be important to take into account the effect of climate change on the spatial correlation of productivity. Exploiting the El Niño–Southern Oscillation (ENSO) shock, they find that an increase in the spatial correlation of crop yields makes the welfare gains from trade more unequal.

2.2. The Measured Effect of Temperature on Other Outcomes

Climate in general, and temperature in particular, affects many other outcomes. A review of the reduced-form literature on the effect of temperature on a variety of outcomes is provided by Dell et al. (2014). In what follows we briefly discuss the effect of temperature on natality, amenities, and conflict.

Global warming changes the geographic distribution of population not only through migration but also through differential natality (i.e., the difference between fertility and mortality). There is evidence of such Malthusian mechanisms dating back to the Little Ice Age in Europe (Waldinger 2022). Even in present-day developing countries, natality is sensitive to climate. Deschênes & Greenstone (2011) estimate that climate change will lead to an increase of 3% in the age-adjusted mortality rate by the end of the century. Because of adaptation, these estimates may be an upper bound. In the United States, there is evidence of such adaptation, both in the cross-section and in the time series. Hotter regions in the United States seem to be better protected against the mortality impact of high temperatures (Barreca et al. 2015). Over time, the mortality impact of days with temperatures above 26.7°C has declined by 75% in the United States, with almost the entire decrease occurring after 1960 because of the diffusion of residential air conditioning (Barreca et al. 2016).

Temperature also affects local amenities. In the United States, people have been found to favor a daily average temperature of 18°C (Albouy et al. 2016). By the year 2100, just from this effect, changes in climate amenities would worsen consumption-equivalent welfare by between 1% and 4%. Incorporating the effect of local temperatures on amenities is therefore important to understand how climate change will affect well-being and migration.

Conflict is also related to temperature. In a meta-analysis of the relationship between climate and conflict, Burke et al. (2015a) find that a one-standard-deviation increase in temperature increases interpersonal conflict by 2.4% and intergroup conflict by 11.3%. Similarly, Ranson (2014) estimates that temperature has a strong positive effect on criminal activity in the United States. His estimates imply that between 2010 and 2099, climate change could cause an additional 22,000 murders.

This evidence on the spatial heterogeneity of climate damages needs to be taken into account when evaluating the economic impact of climate change as well as the potential policy responses. This calls for spatially disaggregated assessment frameworks that model explicitly the most relevant adaptation responses. We now turn to a description of such models.

3. DYNAMIC SPATIAL INTEGRATED ASSESSMENT MODELS: MAIN INGREDIENTS

The empirical evidence discussed so far shows that the impact of climate change is heterogeneous across space. It also shows that some of the key adaptation mechanisms to global warming involve technological innovations as well as the movement of goods or people. If we want to quantify and decompose the economic cost of climate change both locally and globally, and understand how they are affected by changes in the economic environment and policy, we need to go beyond the empirical evidence and develop high-resolution dynamic models that explicitly incorporate these adaptation mechanisms. These models must include not only the effect of climate on the economy but also the effect of the economy on climate. Hence, what we need is a S-IAM. Ideally, such a model needs to be (*a*) global, to account for the global externality generated by carbon emissions; (*b*) spatial, to account for the interactions between locations; and (*c*) dynamic, to account for the protracted effects of climate change. This section describes the main building blocks of such models.

3.1. Endowments and Preferences

We start by describing endowments and preferences.

3.1.1. Endowments. To give a prominent role to spatial heterogeneity in the effects of climate change, consider an economy with a continuum of locations r in two-dimensional space. In each period t, the world is endowed with a certain population, and each location is endowed with a certain amount of land. Because climate change may have an impact on natality (i.e., the difference between fertility and mortality), we may choose to make the world population time-dependent (Cruz & Rossi-Hansberg 2024). The amount of land in a given location might also be time-varying due to climate change. For example, permanent flooding caused by sea-level rise reduces the amount of land available (Desmet et al. 2021).

3.1.2. Preferences. In many economic geography models, the utility of an agent j who lives in location r depends on (*a*) the consumption of goods, $C(r)$; (*b*) the level of local amenities, $a(r)$; (*c*) an individual-specific idiosyncratic preference for the location, $\varepsilon^j(r)$; and, possibly, (*d*) an individual-specific cost of accessing the location, $m^j(r)$. Following this structure and allowing for a time dimension, we can write the period utility of an agent j who resides in location r at time t as

$$U_t^j(r) = a_t(r)\, C_t(r) \varepsilon_t^j(r)\, m_t^j(r)^{-1}. \qquad 1.$$

The period utility is discounted over time using a constant discount rate β. In what follows we discuss different ways of modeling the different elements of the utility function in Equation 1.

3.1.2.1. Consumption of goods. Because market access plays a central role in determining the spatial distribution of population and economic activity, it is important to allow for trade. As we know from standard trade theory, there are two main reasons locations might want to trade with each other: product differentiation and comparative advantage. A simple way to introduce both channels is to have an upper-tier Cobb-Douglas preference structure between different goods and a lower-tier Spence-Dixit-Stiglitz preference structure between different varieties of the same good, as done by Conte et al. (2021). This gives

$$C_t(r) = \prod_{i=1}^{I} \left[\int_0^1 c_{it}^{\omega}(r)^{\rho}\, d\omega \right]^{\frac{\chi_i}{\rho}}, \qquad 2.$$

where c_{it}^{ω} denotes the consumption of variety ω of good i, $1/(1-\rho)$ is the elasticity of substitution between different varieties of a given good, χ_i is the share of good i in the agent's expenditure, and I is the number of goods or industries (in a one-sector model, $I = 1$).

If we are interested only in introducing a role for market access, then having a one-sector model with differentiated goods is enough. Having a one-sector model also suffices if our main focus is on the aggregate effect of climate change on productivity. Of course, the impact of global warming tends to be sector specific (Schlenker & Roberts 2009, Dell et al. 2014, Zhang et al. 2018, Cruz 2023). As a result, the vulnerability of a location to climate change depends on its sectoral specialization: Locations with a large agricultural or construction sector are more sensitive to rising temperatures than locations specialized in services. At the same time, the sectoral heterogeneity in vulnerability to climate change also means that there is scope for adaptation by shifting specialization. The key insight is that global warming operates as a shock to local comparative advantage. In a world with trade, locations can adapt by shifting production away from the sectors that are hit the hardest, with only modest adjustments to their consumption patterns due to transport costs. Costinot et al. (2016) analyze this substitution in the context of different agricultural crops, whereas Conte et al. (2021) focus on distinguishing between agriculture and the rest of the economy.

Another reason for introducing multiple sectors is if our interest lies in the relationship between climate change, economic development, and structural change. It is well known that as countries develop and grow, the expenditure share of agriculture drops. All else equal, a shrinking agricultural sector makes the economy less sensitive to adverse climate shocks. However, if global warming lowers local income per capita, then we get structural change in reverse. A drop in income increases the expenditure share of agriculture, making the economy more vulnerable to rising temperatures and magnifying the negative impact of climate change in less developed countries, particularly if it is costly to trade. Nath (2020), Cruz (2023), and Conte (2023) explore this channel using the nonhomothetic preferences of Comin et al. (2021) to model structural change. In this case, the utility from consuming $C_t(r)$ can be implicitly defined by

$$\sum_{i=1}^{I} \Omega_i^{\frac{1}{\sigma}} C_t(r)^{\frac{\epsilon_i}{\sigma}} C_{it}^{\frac{\sigma-1}{\sigma}} = 1, \qquad 3.$$

where Ω_i are taste parameters for the different goods, ϵ_i are utility elasticities for each good, and σ is the elasticity of substitution between goods.

3.1.2.2. Amenities. Since the seminal work of Rosen (1979) and Roback (1982), local amenities have been central to accommodating real-income differences across space. The idea is simple: If we take a geography characterized by free mobility, then locations with low real income and large populations must have good amenities. As such, allowing for amenities to affect utility is a key ingredient of most economic geography models. Of course, in a world with migration costs, those spatial frictions need to be taken into account when estimating amenities. The easiest way to model amenities is to take them to be a fixed location characteristic: $a_t(r) = \bar{a}(r)$. For instance, one would typically think of natural amenities, such as proximity to water or the type of landscape, as exogenous and constant.

However, in a world with climate change, some of these natural amenities are no longer exogenous and become time-varying. Suppose we take an individual's ideal temperature to be 18°C, as estimated by Albouy et al. (2016). Depending on whether a location's initial average temperature is below or above 18°C, global warming will either improve or worsen local well-being. In addition, rising temperatures may affect a location's amenities in an indirect way: In some locations, lakes may dry out, and in other locations, sea-level rise may affect who gets the ocean view. More generally, a location's amenities will depend on temperature T_t, so that $a_t(r) = \bar{a}(r, T_t)$.

Amenities may also be affected by local density. On the one hand, greater density may increase the local supply of man-made amenities and hence improve the quality of life. The variety of cultural goods and entertainment offerings tends to scale up with population. If the production of such man-made amenities is not explicitly modeled, they would show up as amenities improving with density. On the other hand, greater density may also lead to more crime as well as higher congestion in the enjoyment of some natural amenities, such as beaches or parks. In that case, amenities would worsen with density. A more general expression of local amenities would then be $a_t(r) = \bar{a}(r, T_t)L_t(r)^{-\lambda}$, where a higher value of λ would imply more congestion in amenities.

3.1.2.3. Idiosyncratic preferences. In quantitative spatial models, it is convenient to include individual-specific preferences for a location, $\varepsilon^j(r)$. This helps modulate the sensitivity of migration to income shocks. More specifically, if $\varepsilon^j(r)$ is drawn from a Fréchet distribution, then the shape parameter is equal to the elasticity of migration to real income.

3.1.2.4. Migration costs. For an individual j residing in location s, there is a cost of moving to location r. Migration costs are typically modeled as an origin–destination bilateral fixed cost. To make bilateral moving costs between s and r consistent with our notation, the j superscript in $m_t^j(r)$ can be made specific to the origin of agent j. In a dynamic spatial model with forward-looking agents, a fixed moving cost requires agents to know the distribution of economic activity over space and time for each residential choice. When the number of locations is not too large, solving such a model is feasible using the insights of the dynamic discrete choice literature (Caliendo et al. 2019, Balboni 2021, Rudik et al. 2022).

However, when the number of locations is very large, this approach can be computationally intractable. To address this issue, Desmet et al. (2018) propose a migration cost, $m^j(r)$, that operates as a discount on an agent's flow utility while residing in the destination location r. Here as well, the j superscript can incorporate the origin of agent j—say, s. The difference with the fixed-cost approach is that agent j stops paying the flow utility of moving to r if they move out of r. Desmet et al. (2018) show that this makes the migration decision fully reversible if bilateral migration costs are log-linear in an origin and a destination effect [i.e., for individual j who moves from s to r, $m^j(r) = m(s)m(r)$ for some $m(\cdot)$]. As a result, the agent's dynamic forward-looking migration decision simplifies to a static decision, rendering the model computationally tractable.

3.2. Technology

As mentioned before, for market access to play a role, we assume that the economy produces a continuum of varieties ω of one or more goods i. The Cobb-Douglas production technology of a firm producing q_{it} units of a variety of good i in location r at period t is given by

$$q_{it}(r) = z_{it}(r) \prod_k F_{kit}(r)^{\mu_{ki}}, \qquad 4.$$

where $z_{it}(r)$ denotes total factor productivity (TFP), F_{kit} are inputs of different factors k, with corresponding factor shares μ_{ki} (in the case of perfectly competitive firms, there are constant returns to scale, so $\sum_k \mu_{ki} = 1$). To facilitate notation, Equation 4 ignores variety superscripts, even though TFP may vary across varieties of the same good. In quantitative trade models with many goods and many locations, it is convenient to follow Eaton & Kortum (2002) by assuming that the TFP of a variety ω of good i in location r and period t, $z_{it}^{\omega}(r)$, is the realization of a productivity draw from a Fréchet distribution. This probabilistic approach, together with the law of large numbers, generates a gravity equation that predicts trade flows between locations well. In what follows, we discuss alternative ways of modeling the different elements of the production function in Equation 4.

3.2.1. Factors of production. A simple Ricardian version of Equation 4 would have labor as the only factor of production k. Some models that focus on the impact of climate change on migration distinguish between high-skilled and low-skilled labor (Burzyński et al. 2022).

In economic geography models, where congestion shapes the spatial distribution of economic activity, it is useful to include land as another factor of production. Land also plays a separate role in models of climate change. Global warming can impact both the amount of available land (e.g., coastal areas may suffer land loss through permanent sea-level rise) and the suitability of land (e.g., desertification may make land unproductive for agriculture). Henderson et al. (2023) empirically analyze the impact of climate change on the quality of land.

In addition to land, energy is a key factor of production when modeling the relationship between the economy and climate change. Indeed, the use of energy based on fossil fuels is the single most important contributor to carbon emissions and hence to anthropogenic global warming. Energy intensity differs across sectors, a relevant fact when analyzing the impact of carbon taxes on sectoral specialization (Conte et al. 2022). Of course, energy need not come exclusively from fossil fuels. Hence, we can model energy as a mix of "dirty" and "clean" inputs (Acemoglu et al. 2012). Cruz & Rossi-Hansberg (2024) assume that firms produce their own energy using a constant elasticity of substitution (CES) technology that combines fossil fuels and clean energy sources. These inputs are purchased at a world price, with the price of fossil fuels increasing as their stock is depleted. The elasticity of substitution in this technology is a key parameter, since it governs how changes in the cost of fossil fuels affect their use. A larger elasticity of substitution makes it easier to substitute away from carbon inputs and therefore makes carbon pricing more effective in reducing emissions. Clearly, the elasticity of substitution is itself endogenous and is a function of the characteristics of the technology in use and the type of capital installed in the economy.

In principle, including capital as an additional factor of production is also desirable. Indeed, if we worry about climate change damaging physical capital and infrastructure, then we want to allow this channel to be operative. Because investment decisions are inherently dynamic in nature, introducing capital is complex. Desmet et al. (2021) argue that ignoring capital may be a reasonable simplification when studying slow-moving changes in sea levels. On the one hand, differences in infrastructure and other productivity-enhancing capital can be partly captured by $z_{it}(r)$ without the need to explicitly include capital. On the other hand, the gradual nature of global warming implies that some of its damaging effects will take time to materialize. If so, regular depreciation would reduce the cost of capital destruction.

Of course, when we focus on extreme weather events, like storms, the destruction of installed capital can be immediate. Hence, when studying the economic impact of the increase in the frequency of extreme events generated by climate change, modeling capital investment decisions is essential. Recent work by Bilal & Rossi-Hansberg (2023) finds that anticipating changes in extreme weather events due to climate change induces a large relocation of capital investment. They leverage the Master Equation representation of the economy to develop a tractable spatial dynamic model with forward-looking migration and capital investment decisions. Their approach provides a path forward to fully incorporating forward-looking agents into dynamic spatial models with many locations, though it relies on a first-order approximation around a steady state and to date has only been applied to the United States, without endogenizing the feedback from the economy to carbon emissions.[4] Two other key papers that include capital in integrated assessment

[4]Kleinman et al. (2023) also incorporate forward-looking investment decisions in a quantitative spatial model with trade and migration. They do not focus on global warming, but their model could in principle be extended to a S-IAM.

models are by Kotlikoff et al. (2021) and Krusell & Smith (2022). The former takes an overlapping generations approach with mobile capital to study carbon policy in a multi-region model, whereas the latter includes forward-looking investment decisions in a high-resolution S-IAM. These papers are complementary to some of the other S-IAMs in that they model savings and investment decisions but ignore migration and trade.

3.2.2. Productivity and climate. An important part of any IAM concerns the impact of climate change on the economy. In the DICE and RICE models of Nordhaus (1993, 2008, 2010), climate affects productivity and output through the damage function.

In our context, a simple way of introducing this channel is to make productivity, $z_{it}(r)$, a function of temperature, $T_t(r)$. Thus, we can write $z_{it}(r, T_t(r)) = (1 - g_{it}(r, T_t(r)))\tau_{it}(r)$, where $\tau_{it}(r)$ is productivity in the absence of climate change, and $g_{it}(r, T_t(r))$ is the damage function. Three points are worth mentioning here, two of which we already touched upon in Section 2. First, the sensitivity of productivity to temperature is sector specific. For example, agriculture and construction are more vulnerable to climate change than manufacturing and services (Cruz 2023). As such, it is ideal for $g_{it}(r, T_t(r))$ to depend on i. Second, a country's level of development may reduce the sensitivity of productivity to climate. For example, air conditioning, though coming at a cost, may mitigate the impact of higher temperatures in service and manufacturing jobs. Hence, the impact of climate change on productivity may be smaller in more developed countries (Dell et al. 2012). As such, it is a good idea for $g_{it}(r, T_t(r))$ to depend directly not only on $T_t(r)$ but also on r and t.

Third, in terms of modeling, a relevant question is what specific climate-related variables these damage functions should depend on. After all, climate change may impact not only average temperature but also its distribution. In addition, it affects the frequency of extreme events, such as hurricanes, as well as sea levels. Since all these effects are ultimately a consequence of global warming, sometimes through complex physical relationships, it is reasonable to model sector productivity as depending simply on temperature. Of course, the complex effects of temperature may require making the relationship between productivity and temperature not only sector specific but also location specific: For example, two different locations, both with the same temperature of 28°C, may face different damage functions if one is located on the coast and is more prone to hurricanes than the other. This is another reason for $g_{it}(r, T_t(r))$ to depend on r.

The expression $z_{it}(r, T_t(r))$ allows for a rich and complex relationship between productivity and temperature: It can depend on the specific sector i, the time period t, and the location r. In terms of the functional form of the damage function $g_{it}(r, T_t(r))$, different approaches have been taken. The DICE model assumes a simple quadratic function of global temperature that applies at the global level (Barrage & Nordhaus 2023). The regional RICE model assumes the same functional form but allows the parameters to be specific to 12 different regions in the model (Nordhaus 2010). The work by Conte et al. (2021) assumes a bell-shaped damage function that is sector specific. Given the complexity of the relationship between temperature and productivity, it may be better not to impose any functional form. This is the approach taken by Cruz & Rossi-Hansberg (2024), who estimate a one-sector damage function nonparametrically. Another key question concerns uncertainty about the parameters of the damage functions, an issue analyzed by Barnett et al. (2022).

3.2.3. Innovation. Since climate change plays out over the long and very long run, it is essential to include endogenous local innovations for a variety of reasons. First, since certain locations will suffer more from climate change than others, climate change will lead to a reallocation of economic activity across space. As certain clusters of economic activity decline and others emerge, it is important for these new clusters to be able to endogenously grow over time. Second, economic growth is intimately related to structural transformation. As mentioned before, if climate change lowers income, structural change would magnify the detrimental effect of climate change (Nath 2020). Third, endogenous innovation is also important if we want to model the green transition. This could be accomplished by introducing an energy sector that innovates. So far, there has been substantial work on this green transition in the macroeconomic literature (Acemoglu et al. 2012, 2016), but less attention has been paid to the spatial dimension of this transition. More generally, the literature on directed technical change has not incorporated space.

Modeling endogenous innovation in frameworks with many locations is subject to the same dimensionality issue discussed in the case of migration. Desmet & Rossi-Hansberg (2014) propose a solution whereby any local investment in technology diffuses locally after one period. This, together with local competition for land, ensures that any profits from innovating do not extend beyond the same period. The result is a competitive environment in which firms invest in innovation in order to maximize their current profits and, therefore, what they are willing to bid for land. As such, land, the fixed factor, obtains all the rents from innovation. Importantly, the current profits from innovation depend on the firms' market size, and therefore on the ease of accessing customers around them, which itself is a function of transport costs and the distribution of economic activity. This structure simplifies the dynamic innovation decision to a sequence of static problems, allowing for a tractable solution.[5]

3.2.4. Transportation costs. In most trade models, transport costs are modeled as iceberg costs, implying that the energy (and emission) intensity of transporting a particular good is the same as the energy (and emission) intensity of producing that good. Given the importance of fossil fuels in transportation, it might be useful to explicitly model the transport sector. Doing so would introduce an additional link between trade liberalization, increased transportation, and carbon emissions. While trade may help adapt to climate change, it might also lead to higher emissions through more transportation. At the same time, since trade improves the economy's efficiency, it also allows for producing the same quantity with fewer inputs, including energy. These different issues are discussed in a recent review article by Copeland et al. (2022). However, so far not all of them have been incorporated into S-IAMs.[6]

3.3. The Impact of Energy Use and Carbon Emissions on Temperature

In IAMs, climate affects the economy and the economy affects climate. In our discussion above, we have highlighted different channels through which climate affects the geographic distribution of economic activity and population. In particular, temperature may affect sector-specific productivity, amenities, and natality. These different channels may be time, location, and sector specific.

As for the effect of the economy on climate, it is mainly due to the use of fossil fuels as an energy source. In that sense, the energy mix (fossil fuels versus renewable energy), sectoral specialization (differential energy intensity across sectors), and overall productivity (lower input use, including energy, for the same output in more productive locations) all play a role in determining carbon emissions. How exactly carbon emissions translate into global warming depends on the carbon

[5] In principle, the approach of Bilal & Rossi-Hansberg (2023) could be extended to make the innovation decision forward-looking, thereby incorporating anticipation effects. However, this would require computing the balanced growth path of the economy, which complicates the problem relative to Bilal & Rossi-Hansberg's (2023) model. Furthermore, that methodology is based on first- or second-order approximations that are guaranteed to be accurate only for small shocks.

[6] A separate issue when considering transport costs relates to trade in energy. Because of its increased reliance on the electrical grid, the green transition is bound to reshape energy trade (Arkolakis & Walsh 2023). We discuss this further in Section 7.

cycle and on the sensitivity of temperature to the atmospheric stock of carbon. A simple equation that captures the relationship between energy use, carbon emissions, and the atmospheric stock of carbon is

$$K_t = \varepsilon_1 K_{t-1} + \varepsilon_2 E_t, \qquad 5.$$

where E is energy use in the form of fossil fuels and K is the atmospheric stock of carbon. The parameter ε_2 determines how the use of fossil fuels translates into carbon emissions, and the parameter ε_1 determines the rate of decay of the atmospheric stock of carbon due to the carbon cycle. Note that the variables in Equation 5 are not location specific, because carbon emissions add to the global atmospheric stock of carbon, no matter what their origin is. A second simple equation captures how an increase in the atmospheric stock of carbon affects the average global temperature, T, namely,

$$T_t = T_{t-1} + \nu(K_t - K_{t-1}), \qquad 6.$$

where ν modulates the sensitivity of temperature to the carbon stock. Any change in the average global temperature, T, then translates into differential changes in the average local temperature, $T(r)$. Mitchell (2003) argues that this downscaling relationship is linear, so that

$$T_t(r) - T_{t-1}(r) = \xi(r)(T_t - T_{t-1}), \qquad 7.$$

where $\xi(r)$ measures the increase in temperature in location r for a 1°C increase in global temperature.

Equations 5 and 6 are somewhat simplistic representations of the carbon cycle and of the relation between the carbon stock and temperature. As for the carbon cycle, Nordhaus (2010) uses an expression similar to Equation 5 with $\varepsilon_1 < 1$. This implies that the effect of emissions on the atmospheric stock of carbon decays over time to zero, as the emitted carbon gradually moves to the lower ocean. Allen et al. (2009) and Matthews et al. (2009), instead, argue that assuming zero decay is a reasonable approximation of the carbon cycle. In that case we have $\varepsilon_1 = 1$, and all that matters are cumulative emissions. The consensus seems to lie somewhere in between. Building on work by Archer (2005), Golosov et al. (2014) use a carbon cycle where around 20% of emissions stay in the atmosphere forever. The models of Hassler & Krusell (2012), IPCC (2013), and Cruz & Rossi-Hansberg (2024) are based on carbon cycles with that same feature: Emissions never fully decay. As for the relation between the carbon stock and temperature in Equation 6, a fuller account requires distinguishing between two processes. First, the increase in the carbon stock above preindustrial levels leads to an increase in radiative forcing, implying that the Earth receives more energy than it radiates into space. Second, the increase in radiative forcing affects global temperatures (IPCC 2013).

As more and better climate simulations become available, they should be used to recalibrate the carbon cycle and the temperature response. Folini et al. (2024) provide a state-of-the-art way of doing this, using data from Phase 5 of the Coupled Model Intercomparison Project (CMIP5) that bundles the output of many global climate models. As with damage functions, one overarching concern is uncertainty about the effect of emissions on temperature. This is further discussed by Folini et al. (2024) as well as Joos et al. (2013) and Barnett et al. (2022).

4. QUANTIFICATION OF DYNAMIC SPATIAL INTEGRATED ASSESSMENT MODELS

4.1. Data

S-IAMs at a high spatial resolution come with some data challenges. As an example, Desmet et al. (2021), Conte et al. (2021), and Cruz & Rossi-Hansberg (2024) conduct their analyses at the 1° × 1° grid-cell level for the entire globe, which implies discretizing the world into 64,800 cells. At that level of spatial resolution, they need as inputs data on factors of production, output, and temperature. When it comes to population and output, the Gridded Population of the World (GPW) (see **https://sedac.ciesin.columbia.edu/data/collection/gpw-v4**), the G-Econ 4.0 database, and nighttime light data are possible sources. Disaggregating by sector is more difficult, but splitting total output into agricultural and nonagricultural output is feasible by using data from the Global Agro-Ecologizal Zones (GAEZ)'s Actual Yields and Production data set (see **https://gaez.fao.org/pages/theme-details-theme-5**) (IIASA & FAO 2012). High-resolution temperature data are readily available from the IPCC AR5 Data Distribution Centre (IPCC 2020).

4.2. Parameters

In what follows, we give details on how to parameterize the economic part and the climate part of S-IAMs.

4.2.1. Economic parameters. Parameters for preferences, technologies, trade costs, and migration costs are either calibrated to moments in the data or come from other papers. Desmet et al. (2018) provide an in-depth discussion of the choice of parameters for the economic part of a model similar to the one sketched in the previous section. Given the focus on spatial frictions, a key parameter is the elasticity of migration to economic outcomes. Many papers have provided such estimates (Ortega & Peri 2013, Monte et al. 2018, Adao et al. 2019, Caliendo et al. 2019). Another key parameter in models that feature capital investments is the elasticity of investment to changes in local rates of return. Bilal & Rossi-Hansberg (2023) provide a structural estimate of this elasticity using observed investment responses to storms and heat waves.

4.2.2. Carbon cycle. One way to parameterize Equations 5 and 6 is to target the increase in the atmospheric stock of carbon and the increase in temperature as predicted by the IPCC. Depending on future emissions, the Fifth Assessment Report of the IPCC adopts different trajectories for greenhouse gas concentrations, known as Representative Concentration Pathways (RCPs) (van Vuuren et al. 2011).[7] RCP 8.5 is a high-emissions pathway consistent with fossil fuel–intensive growth, RCP 4.5 is a moderate-emissions pathway, and RCP 2.6 is a low-emissions pathway consistent with the goals of the Paris Agreement. IPCC reports also present more complete parametrizations of the carbon cycle that are easy to incorporate into S-IAMs.

4.2.3. Estimating damage functions. Damage functions are typically estimated by analyzing the relationship between economic variables, such as output or measured productivity, and temperature. One problem with many estimations of damage functions is that these economic variables already incorporate some adaptive responses, such as migration. Suppose we run the following regression,

$$\log(O_t(r)) = \sum_{m=1}^{M} \delta_m T_t(r) \mathbb{1}\{T_t(r) \in \mathcal{T}_m\} + \alpha(r) + \beta_t + \varepsilon_t(r), \qquad 8.$$

where $O_t(r)$ denotes a directly observable outcome at location r in period t, like output or measured productivity (output per worker or per unit of a combination of inputs); $T_t(r)$ denotes temperature; $\mathbb{1}\{T_t(r) \in \mathcal{T}_m\}$ is an indicator function of temperature being in interval $\mathcal{T}_m$; $\alpha(r)$ is a location fixed effect; β_t is a time fixed effect; and $\varepsilon_t(r)$ is an error term. With a panel of data on output (or

[7] In the Sixth Assessment Report of the IPCC, these have been replaced by Shared Socioeconomic Pathways (SSPs), which include more nuance in the economic scenarios but stop short of a full IAM.

measured productivity) and temperature, we can estimate δ_m in Equation 8, namely, the semielasticity of outcome $O_t(r)$ with respect to temperature in locations with temperatures in interval $\mathcal{T}_m$. Note that this semielasticity incorporates the full equilibrium response of the measured outcome to the change in temperature. This includes both direct and indirect effects. For example, in response to a change in temperature, people might move out, thereby decreasing output more than the direct impact of temperature on the underlying productivity and output would. Of course, if the adaptive response depends on the state of the economy, then the estimated semielasticities based on observed outcomes are not stable fundamental parameters.

Including the adaptive response of the economy when estimating the damage functions is problematic if we want to use our structural model to evaluate how the economy responds to specific changes in spatial frictions or climate policies. Of course, if differences in policies between locations are not time-varying, then using panel estimation with location fixed effects might be sufficient. This is, for example, the assumption made by Burke et al. (2015b), who estimate the relationship between output and temperature in 166 countries over the period 1960–2010. However, policies and other characteristics of the economy, including spatial frictions, may change over time, and this can affect adaptive responses. In addition, we may want to run counterfactual exercises to evaluate how adaptation reacts to certain policies. For example, liberalizing migration policy would make it easier for people to move out of a place that is hit hard by climate change. Similarly, trade policy affects how easily a location can adapt to climate change by shifting production from more vulnerable to less vulnerable sectors. Therefore, in a structural model that incorporates these adaptation channels, it is desirable to estimate the damage functions using fundamental characteristics, including fundamental amenities and productivities, rather than directly observed measures like output or measured productivity.

This is the approach followed by Cruz & Rossi-Hansberg (2024), who use the full structure of the model to compute fundamental local characteristics. That is, they estimate Equation 8 but use as the dependent variables productivities and amenities that are fundamental in that they are purged of the modeled adaptive responses. They obtain these local fundamental characteristics by inverting the model for every year when data are available. Namely, they find the fundamental characteristics that make the model exactly match the local data on population and income, given trade and migration frictions. This yields a panel of these fundamental characteristics. **Figure 3** depicts the effect of a 1°C increase in temperature on fundamental productivity (panel *a*) and fundamental amenities (panel *b*) as a function of a location's temperature in January (Northern Hemisphere) or July (Southern Hemisphere). For example, in the case of productivity, in the coldest bin with an average temperature of −38°C, an increase of 1°C leads to a local productivity increase of 7.5%. As the winter temperature increases, the productivity benefits decline, reaching zero for a winter temperature of 2°C and then turning negative. For the warmest bin with an average winter temperature of 26°C, an increase of 1°C leads to a local fundamental productivity drop of 16.6%. The impact of temperature on amenities is somewhat smaller and more symmetric: An increase of 1°C in local winter temperatures increases amenities by 2.5% in the coldest regions and decreases amenities by roughly the same amount in the warmest regions. When using structural models to do counterfactual policy analysis, this way of estimating damage functions is superior to using data on observed output or measured productivity.[8]

4.2.4. Alternative ways of estimating damage functions. The approach to estimating the damage functions outlined above uses the panel dimension of the data and requires observations

[8]Of course, the fundamental characteristics used in the estimation depend on the structure of the model. However, given that the counterfactuals also depend on this structure, no additional assumption is required.

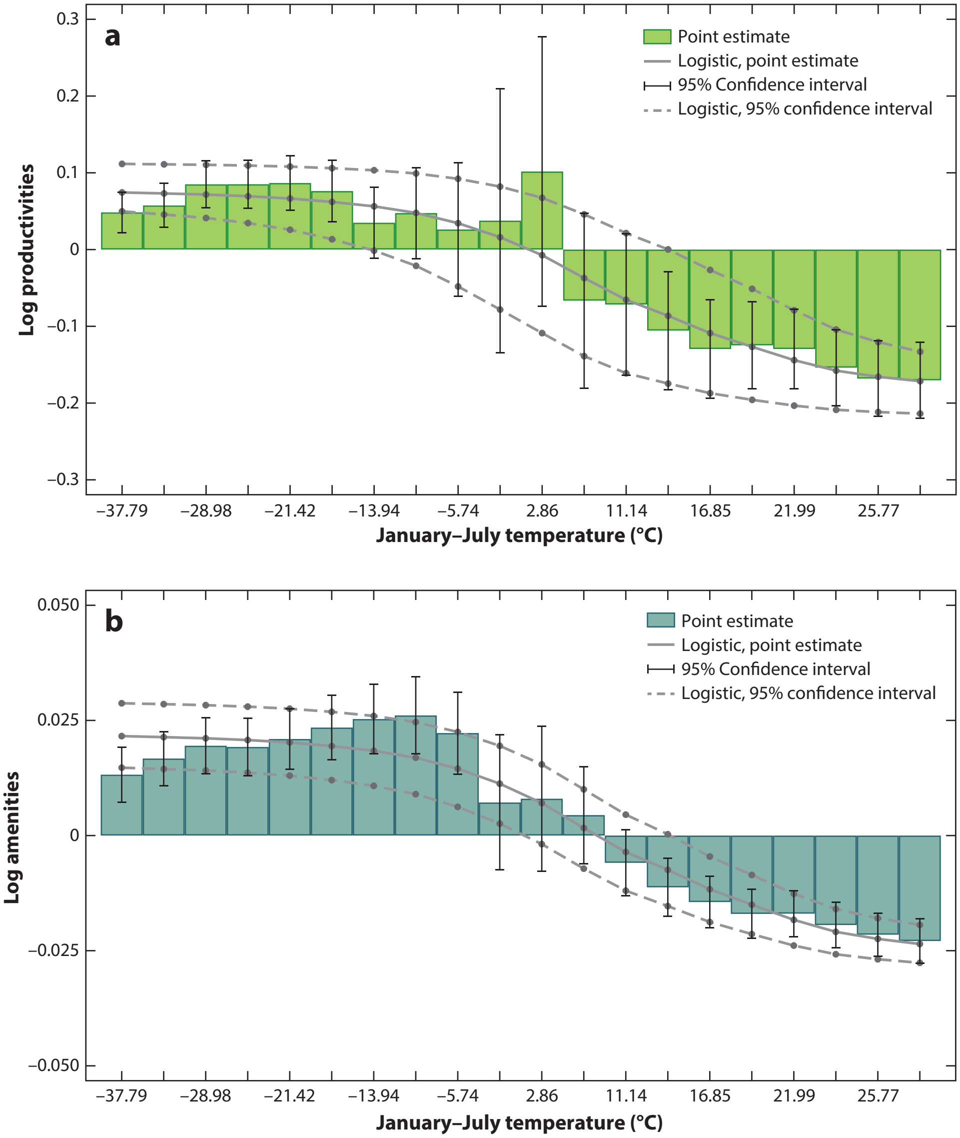

Figure 3

Effect of 1°C increase in temperature on fundamental (*a*) productivities and (*b*) amenities. Figure adapted with permission from Cruz & Rossi-Hansberg (2024).

on local income and population for each year. Instead, Rudik et al. (2022) exploit variation in bilateral trade to estimate the effect of temperature on sector-specific productivity. Using their model's equilibrium conditions, they estimate an equation relating bilateral trade to temperature and fundamental productivity differences. Intuitively, if location s is more productive than location r, then r will import more from s relative to buying from itself. Hence, if temperature shocks in r and s affect relative local productivities, they will also affect the share of expenditure of r on s. This approach allows them to use bilateral trade flows to estimate structural damage functions for fundamental productivities by sector. Because data on bilateral trade flows are plentiful and available at a disaggregated sectoral level, this is a very promising approach. Expanding it to models that feature more adaptation mechanisms is an exciting research agenda. Similarly, Rudik et al. (2022) use the relation between bilateral migration and differences in temperature to estimate the damage function for amenities. Again, by relying on bilateral flows, they expand the size of the relevant data set to estimate the relationship between temperature and amenities. Of course, bilateral migration data are not always readily available, particularly for certain parts of the world.

Another approach is the one used by Krusell & Smith (2022), who calibrate the damage function parameters in their high-resolution S-IAM to match the aggregate damage function in the global DICE model. This procedure yields an inverted-U relationship between temperature and TFP. Although less empirically grounded, this approach has the advantage of being more directly comparable to previous aggregate models.

Bilal & Rossi-Hansberg (2023) propose an alternative methodology to estimate the damage functions. They use an event study design to estimate the input response of investment, employment, and income per capita to extreme weather events, in particular, storms and heat waves. In coastal counties in the United States, they find that large storms generate negative effects on employment and income but positive effects on investment. In their model, this is consistent with storms generating a negative capital depreciation shock. In the case of heat waves, they find significant negative effects on income and, particularly, on population in counties with above-median temperatures. In these counties, the effect on investment is small and negative. These findings are consistent with a combined productivity and amenity shock. Then, to estimate the damage function of temperature through these extreme events within the context of their structural model, the authors proceed in two steps. First, they estimate the damage of a specific event by targeting the impulse response functions. Second, they use a century-long time series on temperatures and extreme weather events to estimate local changes in the probability of extreme events in response to changes in temperatures. This approach has the advantage of targeting adaptive responses directly, but due to the sparsity of large extreme events, it makes conditioning on a detailed set of local characteristics more challenging.

4.2.5. Downscaling global warming.

Projections of future temperature exhibit substantial heterogeneity across space. Cruz & Rossi-Hansberg (2024) use past data from the Berkeley Earth Surface Temperature Database (see **https://berkeleyearth.org/data/**) to estimate the temperature downscaling (Equation 7). They find that for a 1°C increase in global temperature, many places around the Equator have only experienced an increase of around 0.5°C, whereas some areas around the North Pole have witnessed an increase in excess of 2°C (see Cruz & Rossi-Hansberg 2024, figure 4). Krusell & Smith (2022) and Conte et al. (2021) also estimate related downscaling factors. The first paper explicitly aims to match the downscaling factors implied by large climate models. The second paper aims to match some of the IPCC projections. The resulting estimates across these slightly different approaches are small.

5. BASELINE RESULTS AND AN ILLUSTRATION OF THE IMPORTANCE OF GEOGRAPHY

5.1. Heterogeneous Impact Across Space and the Rise in Spatial Inequality

One of the most robust conclusions coming out of S-IAMs is the large heterogeneity across space in the losses that result from global warming. We illustrate this conclusion in the S-IAM of Cruz & Rossi-Hansberg (2024). This model has many of the features described in Section 3, including amenities and productivity depending on temperature through damage functions. In its original version, its quantification is done at the $1° \times 1°$ level, implying that the world is split up into 64,800

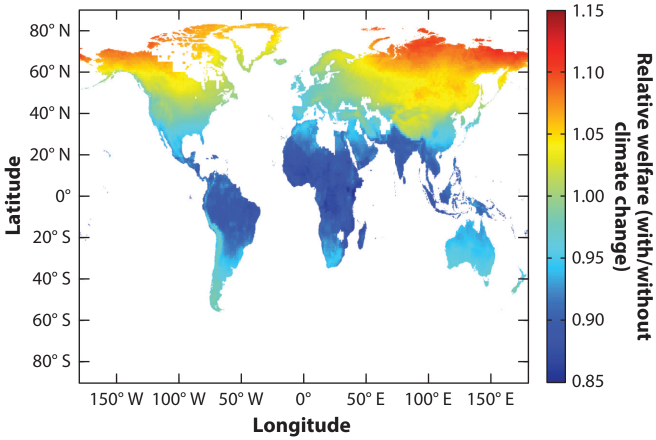

Figure 4

Ratio of welfare with global warming to welfare without global warming in baseline scenario. Figure adapted with permission from Cruz & Rossi-Hansberg (2024).

grid cells, out of which 17,048 have positive land mass. This baseline scenario closely matches emissions and warming implied by the RCP 8.5 scenario.

Figure 4 presents relative welfare with and without global warming for agents living in each of the $1° \times 1°$ cells. Two findings are immediately obvious. First, the losses from global warming are very heterogeneous across space. The map shows losses of as much as 15% in some equatorial regions in sub-Saharan Africa, Southeast Asia, and South and Central America, but gains of as much as 15% in the northernmost regions of the world. This 30% range of variation in the impact of global warming across cells is enormous.[9] Second, global warming causes an increase in spatial inequality. The largest losses accumulate in parts of the world where income per capita today is low. The rich world is marginally affected, since most wealthy areas are located in moderate latitudes. Reflecting this, Cruz & Rossi-Hansberg (2024) estimate that doubling income leads to welfare losses that are on average 1.5 percentage points lower. This relationship is not the result of a different ability to adapt. Rather, it reflects the geography of development in the world economy: The poorest people live in areas that will be the hardest hit.

The results in **Figure 4** incorporate the direct effect of temperature on amenities, productivity, and natality as well as the adaptive responses through trade, mobility, and local innovation. They do not account for other forms of adaptation, other impacts of climate change (e.g., coastal flooding), or the increased frequency of extreme events. Of course, coastal flooding has very heterogeneous spatial effects as well, with many cities in the developing world being in harm's way (Desmet et al. 2021). Storms also tend to affect coastal areas more (Bilal & Rossi-Hansberg 2023). Hence, the phenomena not considered by Cruz & Rossi-Hansberg (2024) would probably further increase the spatial heterogeneity in the effects of climate change. This is also the conclusion of Burzyński et al. (2022), who jointly consider the effect of global warming, sea-level rise, and extreme weather events but without incorporating trade, local investments, or the feedback of the economy on climate. To comprehensively assess the impact of climate change on spatial inequality, more work that includes these different mechanisms is needed.

[9]Krusell & Smith (2022) , Burzyński et al. (2022), and Conte et al. (2021), among others, also find large spatial heterogeneity in damages.

5.2. The Importance of Spatial Integrated Assessment Models with High Spatial Resolution

Although both the impact of climate change and the response to climate change are heterogeneous across space, is it really necessary to have a high-resolution model? Would distinguishing between the world's main regions, as done in the RICE model of Nordhaus (2010), be enough?

To assess the importance of having a high-resolution spatial model, we use the S-IAM of Cruz & Rossi-Hansberg (2024) to analyze the effect of averaging out damages across space. More specifically, we take the damages to amenities and productivities at the $1° \times 1°$ level and average them either at the level of the world's main regions (as classified by the World Bank) or at the level of the entire world. As an example, the productivity damage to a grid cell in Texas would be equal either to the average damage across all grid cells of North America (in the case of averaging at the regional level) or to the average damage across all grid cells of the world (in the case of averaging at the world level). Apart from averaging damages, the rest of the analysis continues to be done at the $1° \times 1°$ resolution.

Ignoring spatial heterogeneity in damages at a fine resolution is potentially problematic along two dimensions. First, it might fail to identify the impact of global warming on spatial inequality. If damages in the equatorial regions of Africa get averaged out with damages in southern Africa, we may be unable to fully capture the rise in spatial inequality. Second, it may also lead to mismeasuring the global impact of climate change. On the one hand, spatial heterogeneity in the impact of climate change introduces a margin of adaptation by relocating population and economic activity from places that lose to places that gain. Averaging out damages between southern Europe and Scandinavia would weaken this margin of adaptation. On the other hand, averaging out damages may also lead to underestimating the global impact of climate change if many people live in areas that are hit hard.

5.2.1. Mismeasuring the local impact when averaging damages. The map in **Figure 5** depicts the present discounted value (PDV) of real GDP when averaging damages at the level of either World Bank regions[10] (panel *a*) or the world (panel *b*), relative to the baseline where damages are measured at the $1° \times 1°$ resolution.[11] Locations marked in red correspond to areas where averaging damages leads to overestimating real GDP, whereas locations marked in blue correspond to areas where averaging damages leads to underestimating real GDP.

In **Figure 5*a***, averaging damages leads to overestimating real GDP in the US South and West, as well as in southern Europe, central Europe, and the equatorial regions of Africa. When averaging the climate-induced changes to productivity and amenities in Florida (a region that faces significant damages) with those in Canada (a region that enjoys gains), Florida loses less. The same occurs when averaging damages in southern Europe with those in Scandinavia and Russia, and when averaging damages in equatorial Africa with those in southern Africa. Conversely, averaging damages leads to underestimating real GDP in southern Argentina, Mongolia, and northern China. When taking the average effects of climate change on productivity and amenities in Latin America and the Caribbean, southern Argentina is hit harder. The same occurs with Mongolia and northern China when averaging the effects of global warming in East Asia. In **Figure 5*b***, averaging damages at the level of the entire world tends to underestimate real GDP at polar latitudes,

[10]The seven World Bank regions that we consider are East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, the Middle East and North Africa, North America, South Asia, and sub-Saharan Africa.

[11]We obtain similar results when we aggregate at the country level.

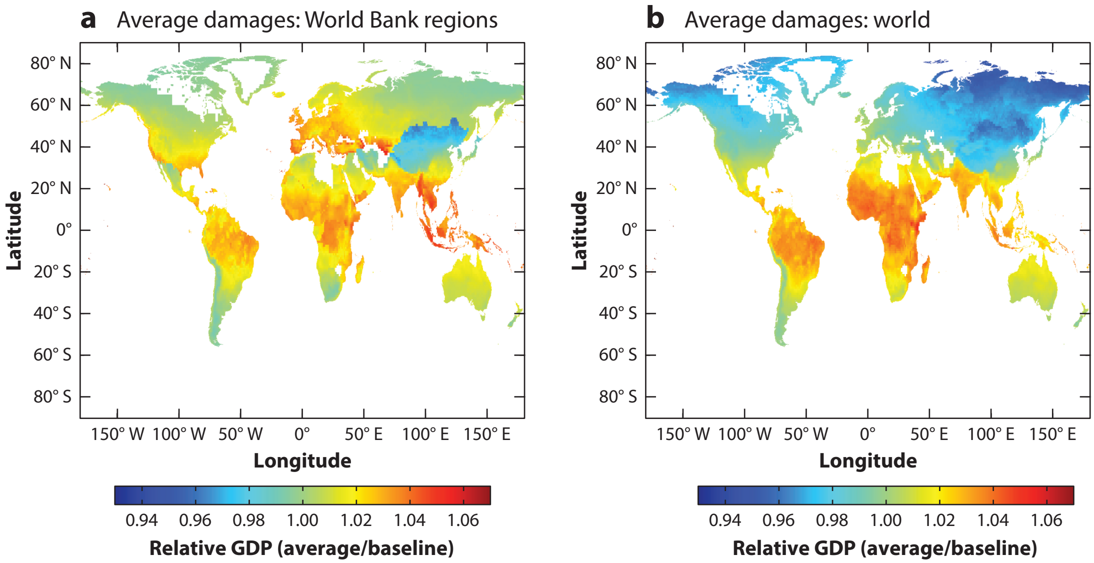

Figure 5

PDV of real GDP when averaging damages, relative to baseline. The maps display the ratio of the PDV of real GDP when averaging direct damages relative to the ratio of the PDV of real GDP in the baseline without averaging. Panel *a* averages damages at the level of seven World Bank regions, and panel *b* averages damages at the level of the world. Abbreviation: PDV, present discounted value.

whereas it overestimates real GDP at equatorial latitudes. As can be seen in **Figure 5*a***, the errors induced by not fully considering the spatial heterogeneity in damages go up to around 6% of the PDV of real GDP. These are relatively large errors, considering that global losses from climate change in the baseline are 3.3% in terms of the PDV of real GDP. In many regions of the world, averaging damages leads to underestimating the cost of climate change. This is particularly true in some of the hardest-hit areas. In sub-Saharan Africa, for example, averaging damages lowers the climate-induced drop in real GDP from 5.4% to 2.9%. Hence, using damages at a low spatial resolution will tend to underestimate the impact of climate change on spatial inequality. We find similar but somewhat amplified effects for welfare, given that the exercise also averages the impact of higher temperatures on amenities.

Overall, averaging damages at the level of either World Bank regions or the entire world eliminates some of the spatial heterogeneity in the effects of climate change. **Figure 6** shows the distribution of the effect of climate change on the PDV of real GDP. In the baseline case where damages are not averaged, we see the effect ranging between −7% and 2%, with an average loss of 3.3% and a standard deviation of that loss of 1.8%. When averaging damages across World Bank regions, the dispersion in the effect drops to between −4% and 2%, with an average loss of 1.3% and a standard deviation of 1.4%. Averaging damages across the world further lowers this standard deviation to 0.4%.

5.2.2. Mismeasuring the global impact when averaging damages.

Figure 7 shows the effect of climate change on global real GDP over time. It compares the baseline, where damages are estimated at the $1° \times 1°$ resolution, to the cases where damages are averaged at the level of either World Bank regions or the world. Two results stand out. First, averaging reduces the peak negative effect of climate change. At the $1° \times 1°$ resolution, world real GDP drops by 5.4% at its peak loss. In contrast, the peak loss drops to 3.8% when averaging the effect of climate change at the level

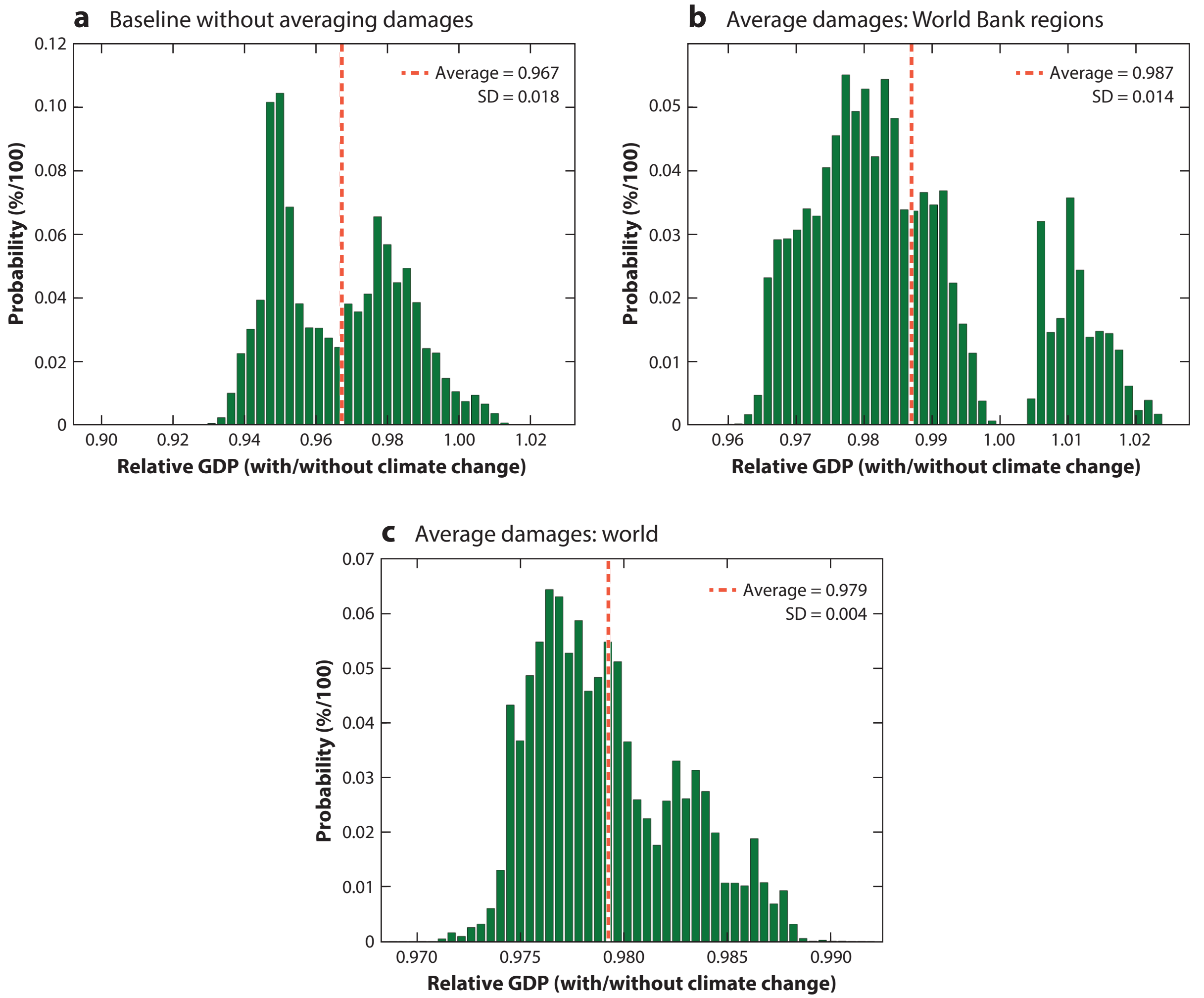

Figure 6

Distribution of the PDV of real GDP with global warming relative to the PDV of real GDP without global warming. Panel *a* is the baseline, without averaging damages; panel *b* averages damages at the level of seven World Bank regions; and panel *c* averages damages at the level of the world. Abbreviations: PDV, present discounted value; SD, standard deviation.

of World Bank regions and to around 3.3% when averaging at the level of the world. With more people living in southern Europe than in Scandinavia, and with more people living in equatorial Africa than in southern Africa, averaging out damages at the level of World Bank regions leads to underestimating the global impact of climate change. This is one reason for the smaller peak losses when averaging damages. Second, in the baseline case, the effect of climate change on global real GDP is nonmonotonic over time. When allowing for heterogeneity in damages, there is scope for adaptation through geographic reallocation from areas that lose relatively to areas that gain. This adaptation contributes to mitigating losses in later periods. Averaging damages at the level of World Bank regions continues to allow for this type of adaptation. In fact, it tends to amplify it, since vast areas in the Northern Hemisphere experience relatively small (or negative) damages. In

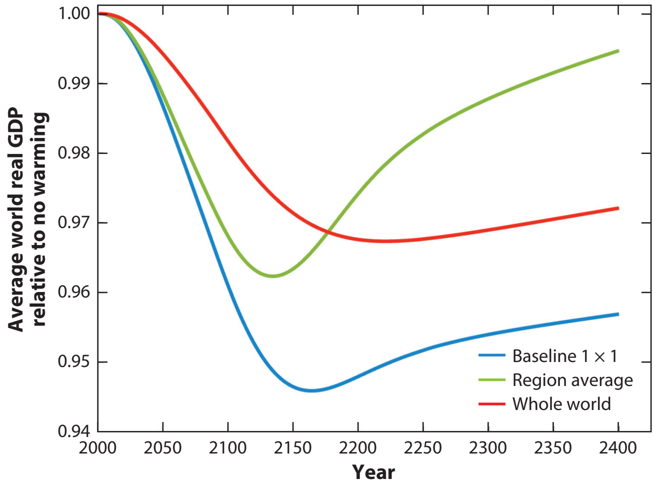

Figure 7

Global real GDP with warming relative to without warming. The figure displays the predicted ratio of world real GDP with global warming to world real GDP without global warming, from the year 2000 to 2400. The three curves represent the baseline case, without averaging damages (*blue*); the case with averaging damages at the level of seven World Bank regions (*green*); and the case with averaging damages at the level of the world (*red*).

contrast, averaging damages at the level of the world diminishes the use of this form of adaptation. In this case, all locations lose, and the nonmonotonicity in the impact of climate change on real GDP over time mostly disappears.

6. GEOGRAPHY AND CLIMATE CHANGE: ADAPTATION AND POLICY

This section illustrates how geography and space play a key role both in adapting to climate change and in evaluating the impact of policies to combat global warming.

6.1. Geography and Adapting to Global Warming

In what follows, we discuss migration, innovation, and trade as adaptation mechanisms to climate change.

6.1.1. Migration. When discussing the Medieval Warm Period, during which temperatures were 1–2°C higher in Western Europe, anthropologist Brian Fagan (2009) describes how people and economic activity migrated to more northern latitudes. He concludes that "the only protection against such [climate] disasters was movement" (Fagan 2009, p. 60). In today's world, anthropogenic climate change is already having a detectable effect on migration and displacement, and future warming is set to exacerbate this phenomenon (Warner et al. 2009).

While migration is costly, it is also a key adaptation mechanism, since not all locations are affected equally by climate change. To assess the importance of migration in adapting to global warming, we need a quantitative model. In an early S-IAM, Desmet & Rossi-Hansberg (2015) analyze the impact of migration restrictions between the Global North and the Global South. In a more recent S-IAM, Cruz & Rossi-Hansberg (2024) predict that a worldwide increase in migration costs by 25% would raise the average welfare cost of global warming by 3% by the

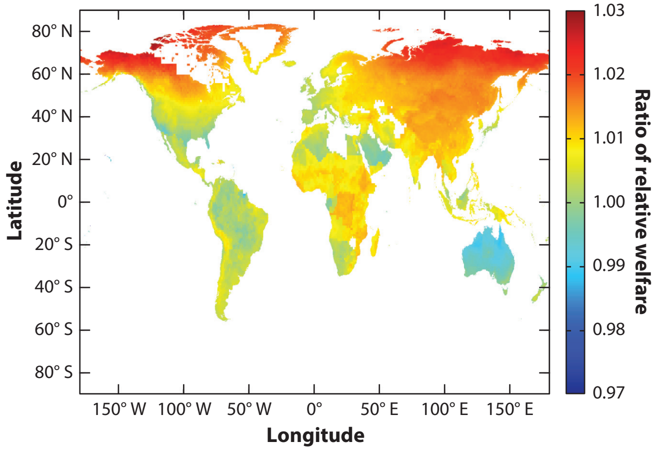

Figure 8

Welfare in 2200: warming relative to no warming in baseline relative to 25% higher migration costs. Figure adapted with permission from Cruz & Rossi-Hansberg (2024).

year 2200 (relative to a baseline welfare cost of 10%). Therefore, in the aggregate, lower migration costs help the world adapt to climate change.[12]

To see which regions gain and which lose from lower migration costs, **Figure 8** plots the difference in the climate-induced welfare effect in the year 2200 between the baseline and a world with migration costs that are 25% higher. In red and yellow are areas where global warming is less costly when migration costs are lower, whereas in blue are areas where global warming is more costly when migration costs are lower. Since overall lower migration costs contribute positively to adaptation, the red areas dominate. However, there is significant heterogeneity. Northern latitudes tend to gain from lower migration costs, because they experience larger economies from density through increased immigration. In contrast, regions in Latin America and Oceania tend to lose when migration costs are lower: They are sparsely populated and lose population, hence making them less attractive for innovation because of shrinking local markets. The findings for Africa and India may be less intuitive: There, lower migration costs also generate benefits. In these already dense regions, lower migration costs allow more out-migration, alleviating some of the existing congestion.

Another quantitative model that assesses the impact of climate change on migration is the one by Burzyński et al. (2022). The authors distinguish between people of different ages and different education levels, although they do not have trade in their model. In their baseline scenario, a predicted 62 million working-age people will migrate over the twenty-first century. Of those, around 15% are high-skilled. In the developing world, most migrants are cross-border movers, whereas in North America and Europe there is a higher stock of within-country movers.

6.1.2. Innovation. As global warming changes the spatial distribution of economic activity, certain economic clusters are likely to decline if no adequate protection is put in place. For

[12] In a seemingly contradictory finding, Bilal & Rossi-Hansberg (2023) show that in the United States migration plays a small role in reducing the aggregate impact of storms and heat waves, although it continues to play a large role in reducing local costs. The reason is that, for the United States, the correlation between the value of living in a given county and the likelihood of that county being affected by extreme weather events is close to zero. Of course, as we have argued above, this is not the case for the world, where direct climate effects will hit the poorest areas much harder. In that case, migration becomes an important adaptation mechanism.

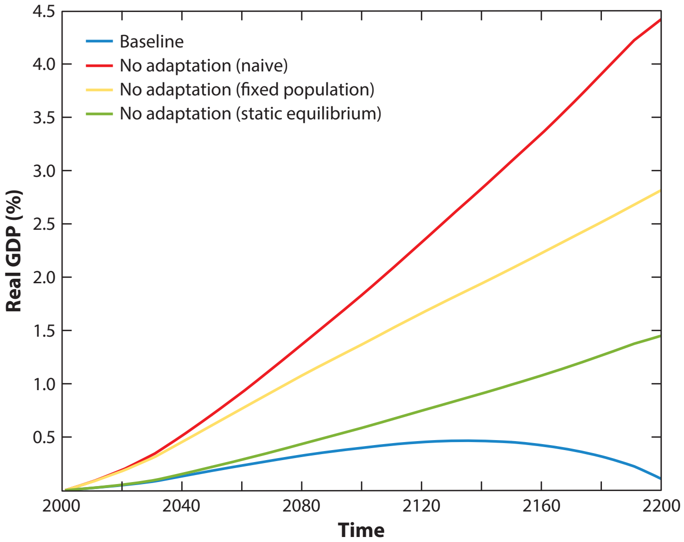

Figure 9

World losses in real GDP due to sea-level rise: different adaptation mechanisms. Figure adapted with permission from Desmet et al. (2021).

example, rising sea levels are expected to severely impact coastal cities, such as Ho Chi Minh City or Bangkok. Since these are highly productive places in their local economies, the associated losses may be substantial. However, as people and firms relocate, new local markets will emerge elsewhere.[13] Growing market size will strengthen the incentives to innovate in these alternative locations. Together with dynamic agglomeration economies, these new clusters of economic activity will benefit from improved productivity growth. This will partly compensate and mitigate the losses experienced in the urban areas that suffer from permanent inundation due to rising oceans.

To what extent do local innovation and agglomeration economies act as an adaptation mechanism to climate change? Desmet et al. (2021) use a S-IAM similar to the one sketched in Section 3 to evaluate the economic cost of coastal flooding over the next two centuries. **Figure 9** depicts the flooding-induced loss in world real GDP between 2000 and 2200. The baseline, represented in blue, allows for adaptation in the form of costly migration and trade, as well as innovation. In this case, the real GDP world losses from sea-level rise peak at around 0.5% in 2140 and decline to 0.1% in 2200. The static equilibrium, represented in green, switches off adaptation through innovation. When ignoring changes in productivity, the real GDP losses in 2200 rise more than threefold to around 1.5%. **Figure 9** includes two more cases. The red curve takes the spatial distribution of real GDP in a counterfactual without flooding, and computes which share is produced in areas that are projected to become inundated. The yellow curve shows the losses from flooding assuming that there is no migration so the distribution of population remains fixed. Overall, the figure illustrates that, in the case of permanent inundation, adaptation can reduce losses by an order of magnitude.

[13]Using data on the global car industry, Castro-Vincenzi (2022) shows how firms reorganize the location of plants to make production more resilient to climate hazards. Similarly, Jia et al. (2022) document that increased flood risk has a large negative impact on firm entry in US counties.

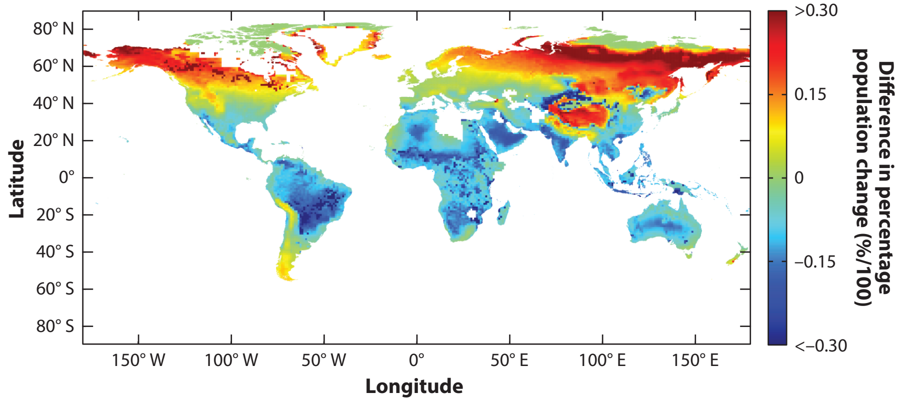

Figure 10

The impact of trade costs on the effect of climate change on population in 2200. The figure displays the difference between high (+50%) and low (−50%) trade costs in the percentage change in population due to climate change. Figure adapted with permission from Conte et al. (2021).

6.1.3. Trade. Because the impact of climate change differs across space and across sectors, we can think of global warming as a shock to the geography of comparative advantage. Hence, an essential way of adapting to climate change is by locally shifting production away from sectors that suffer from a decline in comparative advantage. Of course, global warming also affects absolute advantage: sub-Saharan Africa is likely to lose productivity in virtually all sectors, whereas Canada may gain productivity in almost all sectors. In that sense, we should think of trade as facilitating adaptation, rather than as eliminating the overall impact of climate change. A further complication is that trade and migration interact as adaptation mechanisms: the more the impact of climate change is mitigated through trade, the less need there is for migration.

Conte et al. (2021) evaluate the role of trade (and migration) using a S-IAM with two sectors: agriculture and nonagriculture. Using sector-specific damage functions and the initial spatial variation in temperature and sectoral productivity, global warming changes the economic geography of absolute and comparative advantage across the globe. **Figure 10** maps the difference in climate-induced population change in the year 2200 between a situation with high trade costs (50% above baseline) and a situation with low trade costs (50% below baseline). The red (blue) areas correspond to regions where people move into more (less) due to climate change when trade costs are high. That is, when trade costs are high, there is more climate-induced migration from blue areas close to the Equator to red areas closer to the poles. This suggests that trade and migration are substitutes in their response to climate shocks: higher trade costs limit the scope of adjusting locally by changing sectoral specialization, making adjustment through migration more attractive. Conversely, with lower trade costs, there is less incentive for climate-induced migration, and more people stay in Africa, South Asia, and Brazil.

Because more adaptation through trade implies less adaptation through migration, it is not obvious how much trade liberalization helps to mitigate the overall cost of climate change. On the one hand, lower trade costs imply more scope for local adaptation by changing sectoral specialization. This makes the world less vulnerable to climate change. On the other hand, lower trade costs imply more people continue to reside in the warmest regions that are increasingly hard hit by climate change. This makes the world more vulnerable to climate change. Results in Conte et al. (2021) indicate that the latter (negative) effect dominates in the short run, whereas the former (positive) effect dominates in the long run. When evaluating the role of trade in adapting to climate change, work by Dingel et al. (2019) shows that it is also key to take into account its impact on the spatial correlation of productivity. Ignoring these spatial linkages would lead to understating the climate-driven welfare losses for most countries in Africa.

6.2. Geography and Climate Policy

Different policy instruments can be used to combat climate change: carbon taxes, border adjustment taxes, subsidies to the use of clean energy, and subsidies to innovation in clean energy. In addition to policy instruments that specifically address global warming, many other policies also impact the environment. For example, Shapiro (2021) has documented a systematic antigreen bias in trade policy, with more polluting industries benefiting from lower import tariffs.[14]

While environmental policy has been studied mostly in macro settings, there are some well known spatial aspects to carbon taxation. One spatial aspect relates to the problem of carbon leakage which arises when a country unilaterally introduces stricter environmental regulation. A recent paper that analyzes optimal unilateral carbon taxes in the presence of leakage is Kortum & Weisbach (2021). One solution to carbon leakage are border adjustment taxes, which curb emissions in the rest of the world. Another solution is for environmentally conscious countries to form a "climate club" that collectively introduces trade penalties on noncooperative governments (Nordhaus 2015). Farrokhi & Lashkaripour (2022) study the incentives to form such a coalition in a S-IAM for the world economy, quantified at the country level. They show, for example, that the United States is a critical member of any stable coalition that most countries would want to join. Another spatial aspect relates to heterogeneous incentives to introduce a carbon tax because not all countries lose to the same extent from climate change. In the context of a multi-region overlapping generations IAM, Kotlikoff et al. (2021) show how carbon taxes, coupled with region- and generation-specific transfers, can raise welfare for all generations across all regions.

In addition to carbon leakage and spatial heterogeneity in incentives to introduce carbon taxation, there are other spatial effects of environmental policies that require a S-IAM to be evaluated. Consider an economic geography model, where a carbon tax is introduced by a country (or a group of countries). Because different locations specialize in different industries, and because different industries have different degrees of energy intensity, the introduction of a carbon tax redistributes income and economic activity across space. Because the existence of agglomeration economies and congestion forces implies that the preexisting spatial equilibrium need not be efficient, this spatial reallocation may, under some conditions, improve global efficiency and welfare.

Conte et al. (2022) study this issue in the context of a two-sector $1° \times 1°$ global S-IAM, where they consider the impact of a carbon tax of \$40/tCO_2 introduced by the European Union and rebated locally. With nonagriculture being more energy intensive than agriculture, one might expect a carbon tax to hurt Europe's nonagricultural core. However, the opposite occurs. As long as the trade elasticity is not too high, a large part of the carbon tax is passed on to consumers, many of whom live outside the jurisdiction that implements the tax. Hence, part of the cost of the tax is paid by outsiders, whereas the revenues of the tax go integrally to the locals. As long as the tax is not too large, and therefore not too distortionary, local income increases, attracting immigrants and expanding the local economy. This effect is larger in more energy-intensive regions, and in more productive ones, so a carbon tax causes a reallocation of population and economic activity to Europe's nonagricultural core. Overall, the EU economy expands and grows in terms of population. At the same time, global welfare improves as more people move to some of the world's most productive locations.

[14]A more general discussion of the interaction between trade policy and environmental policy can be found in Copeland et al. (2022).

7. AN AGENDA FOR FUTURE RESEARCH

While important progress has been made in developing dynamic spatial integrated assessment models (S-IAMs), much work remains to be done. Without aiming to be exhaustive, we conclude by mentioning a few areas for future research.

7.1. Green Innovation

There is extensive work in the macro literature on the green transition, and on directed technical change towards clean energy (Acemoglu et al. 2012, 2016). S-IAMs have incorporated innovation in goods using models with high spatial resolution, but so far these models have not focused on green innovation (Desmet & Rossi-Hansberg 2015, Cruz & Rossi-Hansberg 2024). Arkolakis & Walsh (2023) model the combined production and transmission network of electricity with the goal of analyzing the transition to clean energy. However, they model technological innovation in the renewable energy sector as resulting from learning-by-doing. Modeling purposeful investment in innovation would be an interesting addition since these incentives are likely affected by policy. Incorporating directed technical change into a S-IAM with trade and migration seems essential to understanding how the green transition will shape the world's economic geography.

Another related issue concerns the elasticity of substitution between clean and dirty energy. For example, an electric vehicle can get electricity that is generated by either fossil fuels or renewable energy sources. In contrast, a traditional vehicle with an internal combustion engine can only use fossil fuels. Hence, if the stock of vehicles is mostly electric, then the elasticity of substitution between clean and dirty energy will be high, whereas if the stock is mostly combustion engine vehicles, then the elasticity of substitution between the two types of energy will be low. The broader point is that the elasticity of substitution between clean and dirty energy is not a fixed parameter as modeled, for example, in Cruz & Rossi-Hansberg (2024). Instead, it depends on the composition of the stock of capital. Policy can be used not just to affect the production of clean energy, but also the size of the capital stock associated with different energy sources. Endogenizing the elasticity of substitution between renewable sources and fossil fuels by modeling investments in green and brown capital would be an ambitious addition to S-IAMs.

7.2. The Green Transition and Trade in Energy

The green transition will reshape trade in energy and the geography of comparative advantage. As shown by Arkolakis & Walsh (2023), for trade in renewable energy, the electricity grid is essential, making it central to the spatial diffusion of the green transition. Of course, trade in fossil fuels is less dependent on the grid, since the raw materials can be shipped through regular means of transportation. Incorporating energy storage, transmission, and production with a realistic network and realistic local capabilities and inputs to produce fossil and clean energy is an essential missing component of most S-IAMs. Moreover, since the spatial distribution of energy endowments is vastly different for fossil fuels and renewables, the green transition will probably have a profound effect on the geography of comparative advantage.

7.3. Anticipation Effects

Do people and firms take into account future climate change when making decisions? A growing body of empirical work explores this question. For example, Michaels et al. (2021) study whether new construction in the United States avoids low-lying coastal areas, and Weill (2022) analyzes whether new information about flood risk affects the demand for insurance.

Most S-IAMs lack anticipation effects. As mentioned before, the reason is mostly technical. Consider the problem of a resident of Miami who, faced with future climate change, needs to decide whether to stay or go. Her decision depends not just on what might happen in Miami, but also on how climate change will affect all other locations and on the decisions of everyone else. In standard high-resolution S-IAMs, this problem becomes computationally infeasible when the number of locations is very large. Balboni (2021) and Cruz (2023) are two examples of papers that incorporate forward-looking migration decisions and, therefore, worker anticipation, but they do not study the importance of anticipation for their results. Another recent S-IAM that includes forward-looking investment decisions, but no migration decisions, is Krusell & Smith (2022). In recent work, Bilal & Rossi-Hansberg (2023) have made progress on this question. They use the methodology in Bilal (2023) to develop a computationally tractable model with forward-looking migration and investment decisions for the more than 3,000 counties in the United States. They find that anticipation amplifies worker and investment mobility as agents foresee the relatively protracted increase in the frequency of storms and heat waves. They also conclude that anticipation effects in both migration and investment decisions complement and magnify each other. Using these techniques to study the economic impact of climate change on the whole world, while also incorporating the feedback of the economy on climate, would be interesting.

7.4. Uncertainty

There is considerable uncertainty about climate change and its impact. For example, the extent of sea level rise for a given increase in carbon emissions depends on the thermal expansion of the ocean and on the response of the world's main ice sheets (Kopp et al. 2014). A simple way of analyzing this type of uncertainty is to assess the impact of global warming for many different scenarios, some more optimistic and others more pessimistic. For example, Kopp et al. (2014) generate 10,000 Monte Carlo samples to calculate a joint probability distribution of global and local sea level rise. By using 40 stratified paths to assess the spatial economic impact of coastal flooding, Desmet et al. (2021) show the range of possible effects. Similarly, Cruz & Rossi-Hansberg (2024) use the confidence intervals in their estimation of damage functions to assess the uncertainty underlying the predicted impact of global warming.

While useful, this approach is not fully satisfactory, because it does not directly incorporate uncertainty about parameter values, or the distribution of potential damages, into the structural model. In addition, as discussed by Hallegatte et al. (2012), in the context of climate change, decision makers are faced with "deep uncertainty," which extends to uncertainty or disagreement about the model itself. Brock & Hansen (2019) discuss three types of uncertainty. A first is risk (future climate outcomes depend on draws from a distribution, but the probabilities of that distribution are known), a second is ambiguity (uncertainty about how much weight to place on different climate models), and a third is misspecification (the models are imperfect). Hansen & Sargent (2022) bring ideas from robust control theory into statistical decision theory when agents face this type of "deep uncertainty." Clearly, work is needed to bring some of the insights of robust decision-making into S-IAMs.

7.5. Endogenous Migration Frictions and Conflict

Political boundaries are bound to play a large role in the world's response to climate change. First, spatial frictions are not just related to physical transportation costs, but also to political barriers. Many of the models we discussed predict an increase in climate-induced migration. Migratory barriers are of course an endogenous policy variable, and they are likely to respond to changes in migration flows. Understanding this process and incorporating it into S-IAMs is important to gain an accurate understanding of the virtues of migration as an adaptation mechanism. Of course, local climate damages could also lead to conflict between and across countries as individuals fight for access to resources and for the right to occupy land in new regions (Burke et al. 2015a). A model that includes conflict is Burzyński et al. (2022), but more work is needed to properly estimate the impact of climate change on conflict and incorporate it in spatial models in general, and S-IAMs in particular.[15]

7.6. Political Boundaries and Climate Policy Coalitions

There is a mismatch between the countries that contribute the most to carbon emissions and those that suffer the most from climate change. The developed world has created a problem that impacts countries in the developing world especially hard. This differential impact makes reaching a global agreement on curbing emissions more challenging. Partly correcting for this mismatch is the fact that richer countries have a lower marginal utility of income. As a result, the reduction in consumption may be larger in some of the developed world, even if the utility impact of climate change is smaller. More specifically, Cruz & Rossi-Hansberg (2024) show that some areas in the south of the United States and southern Europe have a higher "local social cost of carbon" than most areas in the developing world. Understanding the incentives of different regions to join coalitions to implement global climate policy is essential. Since countries will primarily act based on their individual incentives, understanding the spatial distribution of the willingness to pay for climate policy and its impact on forming policy coalitions is crucial. Farrokhi & Lashkaripour (2022) study some of these issues. Expanding their study to S-IAMs with more adaptation mechanisms is, we believe, promising.

7.7. Conclusion

Although great progress has been made in developing sophisticated S-IAMs in the last decade, we expect this literature to grow substantially in the next decade. We hope to see new studies incorporating more impacts of climate change, refining parameter estimates, including new adaptation mechanisms, and designing novel, and perhaps spatially heterogeneous, policies.

DISCLOSURE STATEMENT

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