The Economic Effects of Climate Change in Dynamic Spatial Equilibrium

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Abstract

We develop a dynamic-spatial equilibrium model to quantify the economic effects of climate change with a focus on the United States. We find that climate change reduces US welfare by 4% and global welfare by over 20%. Market-based adaptation through trade and labor reallocation increases US welfare, but with substantial spatial heterogeneity. Adaptation through labor reallocation and trade are complementary: together they boost welfare by 50% more than their individual effects. We additionally develop a new dynamic envelope theorem method for measuring welfare impacts in reduced form and to validate our quantitative model. We find that welfare distributions from our two approaches are consistent, indicating that our quantitative model captures the first-order factors for measuring the distributional impacts of climate change. The level and distribution of the economic impacts of climate change depends the sectoral and spatial structure of the economy, and the extent to which different markets can adapt.

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Climate change will significantly alter Earth and the global economy. Increased prevalence of extreme heat is already affecting exposed industries, reducing productivity heterogeneously across sectors and space and propagating through supply chains (Burke, Hsiang and Miguel, 2015; Colacito, Hoffmann and Phan, 2018; Diffenbaugh and Burke, 2019; Ortiz-Bobea, Ault, Carrillo, Chambers and Lobell, 2021; Politico, 2021; The Washington Post, 2021). In response to past and expected future climate impacts, individuals and firms have begun adapting by way of market-based mechanisms. People are migrating in response to climate-induced extreme weather and disasters (Missirian and Schlenker, 2017; The New York Times, 2020; The Nation, 2021), jobs are reallocating away from the industries most sensitive to extreme heat (The New Republic, 2021), and trade and trade policy are increasingly in policy conversations as potential levers for dealing with climate change (The New York Times, 2021). Ultimately, the economic impact of climate change depends on how sensitive different industries are to long run changes in temperature, the industrial and spatial structure of the economy, and the extent to which different markets can adapt to changes in global climatic conditions.

In this paper we present two novel approaches for analyzing the economic effects of climate change in a dynamic spatial setting. In our first approach, we develop a dynamic spatial multi-industry general equilibrium model to quantify the impact of climate change on welfare, employment, and reallocation. In our quantitative model, daily average temperature affects annual productivity heterogeneously across different sectors (Dell et al., 2012; Burke et al., 2015; Colacito et al., 2018), and also directly impact the utility of households through local amenities.[1]

Our quantitative framework builds on the dynamic multi-industry trade model by Caliendo, Dvorkin and Parro (2019), where locations are spatially linked through trade as in Eaton and Kortum (2002), and households are dynamic decision makers as in Artuc, Chaudhuri and McLaren (2010). Forward-looking households can adapt to climate change by changing their industry of employment, and in the US, through interstate migration.[2] Production and the flow of goods can also reallocate across space in response to climate-driven changes in productivity. We leverage this structure to quantify climate change's impacts on welfare, migration, and employment, and to unpack the role of market-based adaptation and the structural assumptions underpinning the model.

In order to link the quantitative economic model to the climate, we develop new estimation strategies that leverage the model's macro-structure to estimate the productivity and

[1]Our paper addresses recent calls by economists for a better understanding of the economic impacts of adaptation and extreme events (Burke et al., 2016).

[2]The restriction of migration to the US is due to data limitations in other countries. Data limitations also restrict us to assume free mobility across industries in non-US countries.

utility effects of temperature – or any general weather variable – accounting for dynamic and spatial interactions. By using the model itself to derive the estimating equations, we are able to obtain internally consistent estimates which reflect the fact that households and trade patterns adjust to temperature shocks. By extension, these empirical estimates ensure that our simulation results reflect the actual welfare impacts of climate change given the model's assumptions.

Our approach for estimating the effect of temperature on sector-specific productivity exploits variation in bilateral trade flows across countries relative to own expenditures.[3] The presence of spatially correlated productivity shocks biases estimation of productivity effects in common approaches using variation in GDP. This channel for bias only reveals itself in a spatial equilibrium model. Our estimates indicate that aggregate productivity has a robust, non-linear relationship with daily temperature indicating productivity is marginally sensitive to extreme cold, but is very sensitive to extreme heat. If a single day of the year at the optimal productivity temperature 18°C is replaced by a day at 36°C, productivity declines by 0.9 percentage points. We also estimate sector-specific response functions and find substantial heterogeneity in climate impacts across three different sectors both in terms of optimal temperature and sensitivity to extreme heat. Sectors that are more exposed to the elements such as agriculture and manufacturing are more sensitive to heat. The sector least sensitive to hot temperatures is services.

The second channel for temperature impacts on the economy is through local amenities.[4] We estimate the effect of temperature on local amenities and flow utility with a sufficient statistics representation of the household Euler equation. This specification identifies effects on amenities using variation in migration flows, wages, and distributions of daily temperature across locations. We find that the amenity response function is inverse-U-shaped in daily temperature indicating that households dislike extreme hot and cold. Replacing a single day at the optimal amenity temperature of 15°C with a hot day at 33°C results in a decline in welfare of 1.1 percentage points.

To generate our quantitative results, we simulate the model using the dynamic hat algebra technique introduced in Caliendo et al. (2019). We shock the model from 2015–2100 with the daily temperature distribution from the Representative Concentration Pathways (RCP) 4.5 climate change scenario and compare outcomes versus a counterfactual where the distribution

[3]The normalization of expenditures on goods from another country by own-expenditures eliminates bias caused by correlated spatial patterns in temperature shocks and multi-lateral trade effects. Our specification is similar to that of Jones and Olken (2010), however they do not normalize by own expenditures which is necessary for clean identification. Appendix D.3 demonstrates how standard partial equilibrium approaches are confounded by spatial linkages.

[4]For example, households have preferred temperatures, and extreme heat or cold may affect the value of local amenities like parks or air quality.

of daily temperature is held constant.[5] The RCP 4.5 scenario is consistent with current national climate policies and results in global average warming of 2.5°C – 3.0°C by 2100.

In the simulations we first compute the expected future impacts of climate change on migration and employment within the US, as well as welfare for all countries and US states. Second, we show that capturing certain real world features often missing in quantitative economic evaluations of climate change – input-output linkages from use of intermediates and within-year temperature variability – are first-order factors for welfare and other outcomes. Third, we decompose the role of market adaptation to climate change. Fourth, we test the validity of the quantitative model assumptions by comparing the distribution of welfare predictions against our second, reduced form approach.

In our basic model – which omits market adaptation and novel structural features for quantitative climate-economy models like input-output linkages – climate change results in welfare gains in colder parts of Europe and North America, but significant losses elsewhere. The global impact is a welfare loss of 4.9%, while the US has welfare gains of 1.9%. In our full model, which includes all the structural features, climate change reduces US welfare by 4% and reduces global average welfare by over 20%. We decompose the welfare impact of different structural features and find that sectoral heterogeneity in temperature sensitivity, daily temperature extremes and input-output linkages are all important for determining welfare.

Market-based adaptation has moderate positive aggregate welfare effects in the United States. US workers gain from adaptation by migrating north where temperatures are better for amenities and productivity and moving into industries paying higher relative wages in a warmer world. We quantify the value of adaptation by simulating the welfare impacts of climate change in a model where a particular adaptation mechanism is free to adjust to the climate shocks versus one where we hold its trajectory fixed to its equilibrium trajectory without climate change. Individually, trade boosts aggregate welfare by 0.67pp while labor reallocation has little aggregate effect, however the aggregate masks enormous regional heterogeneity with significantly larger welfare effects. Trade actually worsens welfare in the South by intensifying competition, and labor reallocation worsens welfare in the North through pecuniary externalities on local wages. Trade alone is regressive across regions and labor reallocation alone is progressive. When combined, the market-based adaptation mechanisms increase US welfare by 1 percentage point – more than the sum of their parts because of complementarities between trade and labor reallocation. The total distributional effect is

[5]The RCP scenarios are greenhouse gas concentration trajectories used in the Intergovernmental Panel on Climate Change (IPCC) reports. We use multiple RCP 4.5 global climate models to account for the differences across them in regional predictions of warming (Auffhammer et al., 2013).

progressive.[6]

Like all quantitative models, ours relies on a set of assumptions about functional forms, the structure of the economy, and how climate change impacts the economy. In our second approach, we develop an alternative method: a simple yet powerful reduced form estimator for identifying the welfare effect of a change in climate using weather variation. Our method extends previous work grounded in the envelope theorem. The envelope theorem implies that for an optimized variable, variation in weather is isomorphic to variation in climate (Deschênes and Greenstone, 2007; Hsiang, 2016; Deryugina and Hsiang, 2017). We advance the envelope theorem-based literature by explicitly introducing dynamic and spatial behavior by modeling the household objective as a dynamic discrete choice expected welfare-maximization problem, and showing how to recover the optimized dynamic spatial welfare function using observable data. The advantage of having both quantitative and reduced form approaches is that we can compare welfare predictions from two different models, one with a significant amount of structure and the other without. This comparison helps shed light on whether the structural assumptions underlying our quantitative model – and other similar quantitative models – are appropriate.

The key intuition behind using the envelope theorem in a dynamic setting is that in-migration flows, conditional on a set of fixed effects, are a sufficient statistic for a household's expected future welfare. Regressing the share of households from some other location that migrate to location i on i's temperature will then identify the welfare effect of a long-run change in the temperature component of i's climate. Our set up requires minimal assumptions and allows us to remain agnostic about whether there are growth or level effects on productivity, the households' preferences for temperature, and whether firms adapt via capital investments like air conditioning in addition to purely market-based mechanisms. Our estimates show that welfare is extremely sensitive to extreme heat and marginally sensitive to extreme cold.[7]

We test the assumptions of our quantitative model by simulating it and the reduced form model with the same climate change scenario. If the additional assumptions imposed by the quantitative model are a good approximation to reality, then region-specific welfare should be similar for both approaches. We find that the distribution of welfare differences across regions are extremely close across the two approaches, but the level of the quantitative

[6] Labor reallocation essentially allows workers to use trade competition to their advantage by switching into industries or locations where expenditure shares on their products increase.

[7] Although envelope theorem approaches are attractive because they require a light set of assumptions, they only identify how climate change affects optimized payoffs. Understanding other important economic aspects of climate change – for example, changing migration patterns or industrial specialization – requires imposing more structure.

welfare estimates are consistently positively biased relative to the reduced form estimates. This is consistent with our assumption of perfect foresight in the quantitative model – used for computational tractability – as well as the fact that we only focus on impacts on productivity and amenities. The fact that the quantitative model is capturing the margins of heterogeneity and geography that are important for quantifying the distribution of climate change impacts gives us confidence in the results it generates. One caveat is that the negative effects of climate change may be understated in our quantitative model. This caveat applies to all quantitative models of climate change that must take a stand on precisely how climate change affects the economy.[8]

We contribute to a nascent literature at the intersection of climate impacts, geography, and trade. This literature has often focused on the agricultural sector and found that within-country and between-country reallocation matters (Costinot et al., 2016; Baldos et al., 2019; Nath, 2020; Gouel and Laborde, 2021). Recent work on the geography of climate change has put extra focus on the dynamics. Dynamics are important for correctly understanding the economic impacts of sea level rise, for constructing spatially detailed integrated assessment models, and for identifying how migration responds to changes in climate (Desmet and Rossi-Hansberg, 2015; Balboni, 2019; Conte, Desmet, Nagy and Rossi-Hansberg, 2020; Cruz and Rossi-Hansberg, 2021; Cruz, 2021; Desmet, Kopp, Kulp, Nagy, Oppenheimer, Rossi-Hansberg and Strauss, 2021).[9]

Our work is complementary and advance this literature in several ways. First, we consider a granular set of 20 industries within 3 sectors and allow for worker nonemployment. Second, we use our framework to quantify the value of several adaptation mechanisms and the importance of representing different structural features of the economy and climate. Third, we show that extreme temperature, input-output linkages, and industrial heterogeneity matter for welfare. Fourth, we use the rich structure of our model and a small set of observable variables to empirically estimate impacts of temperature in an internally consistent way, contrasting with papers that obtain estimates from partial equilibrium models.[10]

[8] Although our quantitative model includes substantial detail on reallocation and impacts on productivity and amenities, it does not account for capital destruction, mortality costs, or firm-side adaptive capital investments which previous work has shown plays a significant role in the costs of climate change (Bakkensen and Barrage, 2021; Carleton et al., 2021).

[9] Efforts similar to ours have aimed to bridge the gap between micro-estimates and macro-modeling of the growth effects of natural disasters (Bakkensen and Barrage, 2021), and to measure the spatial equilibrium impacts of environmental regulation (Aldeco, Barrage and Turner, 2019; Hollingsworth, Jaworski, Kitchens and Rudik, 2022).

[10] Other papers in this literature also aim to link impact estimation with the model structure itself. Cruz and Rossi-Hansberg (2021) estimate the productivity and amenities impacts of average decadal winter temperature by inverting their full model to recover the levels of productivities and amenities to use in a linear regression. Nath (2020) derives an estimating equation using a partial equilibrium condition along with data on daily temperature instead of winter averages in order to better capture variability and extremes.

Our estimation approach also allows us to circumvent the need to calibrate the full general equilibrium model, thereby reducing the influence of other modeling choices while at the same time allowing us to speak to the empirical climate literature. Estimating a single equilibrium condition is a simple procedure that can be readily implemented by researchers interested in applying these techniques solely for impact estimation and not for simulating a full dynamic spatial model.

We also contribute to the empirical climate literature by providing two new empirical frameworks. An aim of the current literature is to understand under what conditions simple fixed effects regressions of observable variables on weather identifies how firm or consumer welfare respond to a change in climate – which we can think of as the long run distribution of weather (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Deryugina and Hsiang, 2017; Mérel and Gammans, 2018; Lemoine, 2021).[11] Several of the papers in this literature rely on a static envelope theorem, however, most dynamically optimized variables – such as streams of discounted expected utility – are not directly observed in the data. In our reduced form approach we show that a simple yet general model delivers an equation where bilateral migration shares and fixed effects are sufficient statistics for the present value of a representative household's stream of discounted expected utility. We can then take advantage of the envelope theorem by regressing migration shares on temperature and fixed effects to identify the effect of a change in climate.

In our quantitative approach, we provide a way to recover well-identified estimates of the marginal impact of a change in the distribution of local weather on productivity and flow utility, two non-optimized variables of interest to economists. One attractive feature of our approach is that our specifications clearly show how and why dynamics and spatial linkages matter for identifying how weather affects productivity and utility. Our results show that spatial linkages bias estimates of impacts of extreme weather toward zero and ignoring dynamic behavior biases the estimated optimal amenity temperature downward.

The paper proceeds as follows. Section 1 develops our quantitative model. Section 2 presents our estimating equations for the effects of temperature on productivity and flow utility. Section 3 presents our quantitative results. Section 4 presents the reduced form, envelope theorem-based approach and compares against the quantitative approach. Section 5 concludes. The appendix describes our data in more detail; provides the full derivation of

[11] In other related work, Colacito et al. (2018) estimate the effect of temperature on growth in the United States and explore heterogeneity across sectors and states without microfounding their approach, Newell et al. (2021) take a machine learning approach to understand out-of-sample predictive power of different specifications, Dell et al. (2012) and Burke et al. (2015) estimate the impact of temperature shocks on global production, Burke and Emerick (2016) introduce a long differences technique to get at farmer adaptation, and Mullins and Bharadwaj (2021) show how temperature shocks induce migration in the United States.

estimating equations, welfare, and the simulation algorithm; and presents robustness checks and additional results.

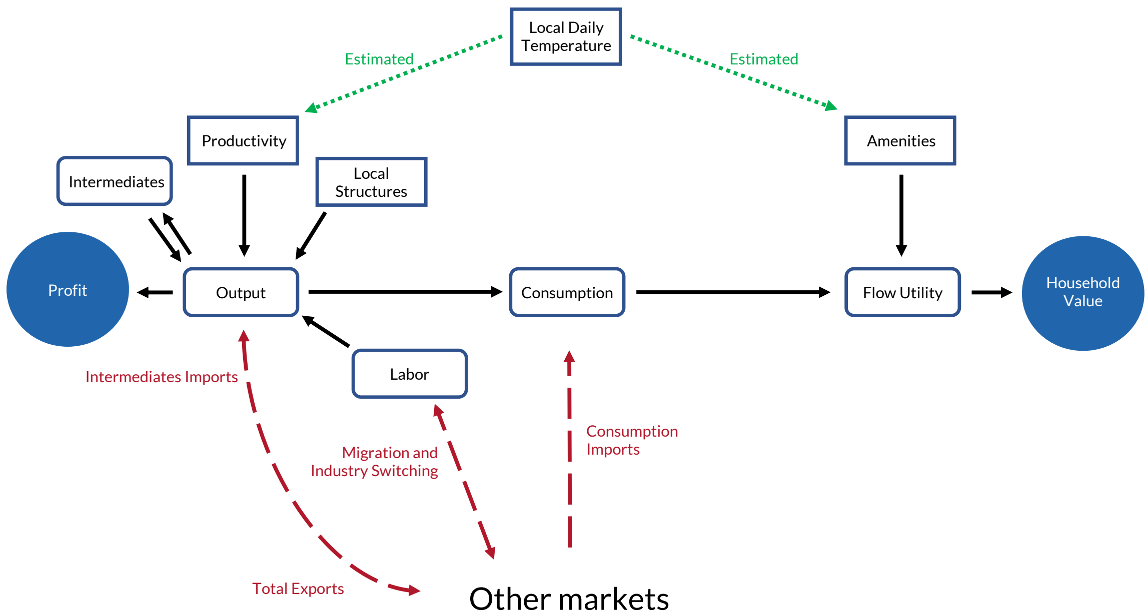
1 A Dynamic Spatial Quantitative Model with Climate Change

Our quantitative model builds on the dynamic forward-looking setting of Caliendo, Dvorkin and Parro (2019, henceforth CDP), augmented to allow for weather effects on local productivity and amenities. Our economy has N regions indexed by n, i, and l; and K industries indexed by k, s, and h. In our quantitative analysis, regions will consist of countries and US states. Each market is defined as a region-industry. Each industry is composed of a continuum of goods or varieties $\xi \in \Xi \equiv [0, 1]$, and goods markets are all competitive.

Figure 1 depicts the high-level structure of the model for a single market-year (region-industry-year). In each market, profit-maximizing firms produce different goods or varieties ξ using a constant returns to scale production technology with labor, immobile and non-accumulating capital which we call local structures, and intermediate inputs. Firms sell their output to other firms for use as intermediate inputs and to households for consumption. As in Eaton and Kortum (2002, henceforth EK), productivity for good ξ in any market is independently drawn from a Fréchet distribution with an industry-specific productivity dispersion parameter θ^k. The distribution of daily temperatures in a region-year affects local productivity, potentially differently across industries.

Time is discrete and denoted by t. In our model, each time period t represents one year. In each period, households work and receive the marginal product of their labor which they spend on consumption. Households cannot save so they spend their full real wage each period. In each period, the households also receive utility from local amenities specific to their current region. Each household's objective is to maximize the expected present value of the sum of future flow utilities from consumption and local amenities, where local amenities depend on local temperature. In a similar spirit to Artuc, Chaudhuri and McLaren (2010), households are forward-looking, and optimally decide the market in which to work and live in each time t given the current distribution of labor and amenities across markets. Households make decisions to migrate or switch industries based on bilateral costs of moving across markets, expected real wages and amenities in each market, as well as the idiosyncratic shock they receive in each market. We now formally describe each segment of our economy, beginning with households and then firms.

Figure 1: The structure of the quantitative model.



Boxes correspond to exogenous quantities, rounded boxes are endogenous quantities. Circles are objectives that are being maximized. Green dotted arrows are the temperature response functions that we will estimate. Red dashed arrows denote the margins of adaptation that we will hold fixed to their no climate change trajectories to decompose the benefits of adaptation.

1.1 Consumption and Labor Supply

In our model households make two types of decisions: consumption choices and forward-looking migration decisions. We begin with their consumption choices. At each time t, households in each region either supply their one unit of labor inelastically to a specific industry, or are nonemployed and engage in home production ($k = 0$). Households who are employed receive a competitive, industry-specific market wage $w_{n,t}^k$ equivalent to the value of their marginal product of labor, while nonemployed households in home production receive a level of consumption $C_{n,t}^0 = b_n > 0$ that is region-specific and time-invariant. Employed households in each region optimally allocate income according to preferences defined by:

$$U(C_{n,t}^k, B_{n,t}) = \log\left(B_{n,t}\, C_{n,t}^k\right)$$

where $B_{n,t}$ is the local amenities in region n at time t. We assume that $B_{n,t}$ is multiplicatively separable in a vector of weather variables $\mathbf{T_{n,t}}$:

$$B_{n,t} = \bar{B}_{n,t} \exp\left(f(\mathbf{T_{n,t}}; \zeta_{\mathbf{B}})\right) \tag{1}$$

where $\bar{B}_{n,t}$ captures exogenous non-weather amenities, $\exp\left(f(\mathbf{T_{n,t}};\zeta_{\mathbf{B}})\right)$ is the weather component of amenities, f is an arbitrary function of $\mathbf{T_{n,t}}$, and $\zeta_{\mathbf{B}}$ is a set of parameters to be estimated that govern how weather affects local amenities.

Households in market (n,k) at time t consume goods from each industry s, $c^{ks}_{n,t}$, which aggregates to an overall basket of goods from different industries given by:

$$C^{k}_{n,t} = \prod_{s=1}^{K} \left(c^{ks}_{n,t}\right)^{\alpha^{s}} \tag{2}$$

where $\alpha^s \in (0,1)$ for all s is the consumption share of goods from each industry with $\sum_{s=1}^{K} \alpha^s = 1$. Each industry bundle $c^{ks}_{n,t}$ is a constant-elasticity-of-substitution (CES) aggregate of all varieties with elasticity $\sigma^s > 0$. The ideal price index is then given by the standard Cobb-Douglas aggregator:

$$P_{n,t} = \prod_{s=1}^{K} \left(P^{s}_{n,t}/\alpha^{s}\right)^{\alpha^{k}} \tag{3}$$

where $P^s_{n,t}$ is the price index of goods purchased from industry s for final consumption in location n, as defined later on. Note that all households in region n, regardless of the industry they work in, face the same price index.

We now present the intertemporal migration decisions of the households. In the initial time period there is a mass of $L^k_{n,0}$ households in each region n and industry k. Households are forward-looking and discount the future at a common rate $\beta \in (0,1)$. In each time period t, households residing in region n and working in industry k supply their one unit of labor inelastically, receive wages or home production, and make consumption decisions, as described above. Households then observe the conditions of the economy and climate in all labor markets, and the realization of their own idiosyncratic shock $\epsilon^s_{i,t}$. At the end of each time period, households choose whether to relocate to another market (i,s) in the same country. Relocating incurs migration costs μ^{ks}_{ni} that are time-invariant, specific to each origin-destination pair of markets, and measured in terms of utility.[12]

Households will choose to move to the market (i,s) with the highest present value stream of future expected utility minus any migration costs. The optimization problem for a house-

[12] For the purposes of our empirical and quantitative application, we only observe migration flows in the US and thus cannot identify μ^{ks}_{ni} in other countries. As a result we assume that there is no migration across countries. We further assume that $\mu^{ks}_{ni} = 0$ for all $n = i$ outside the US so that there is free mobility to switch into different industries. Since the non-US countries have no sub-country representation, there is no within-country migration across regions.

hold in market (n,k) at time t is:

$$v_{n,t}^{k}=\max_{\{i,s\}_{i=1,s=0}^{N,K}} U\left(C_{n,t}^{k},B_{n,t}\right)+\left\{\beta\mathbb{E}_{\epsilon}\left[v_{i,t+1}^{s}\right]-\mu_{ni}^{ks}+\nu\epsilon_{i,t}^{s}\right\} \tag{4}$$

$$C_{n,t}^{k}\equiv\begin{cases} b_n & \text{for } k=0\\ w_{n,t}^{k}/P_{n,t} & \text{otherwise}\end{cases}$$

where $v_{n,t}^{k}$ is the time t welfare for a household in market (n,k), ν is a scalar that captures the migration elasticity of households across markets, and $\mathbb{E}_{\epsilon}$ is the expectation over the household's future realizations of the idiosyncratic shock. Although the model framework admits stochasticity in states and rational expectations, we assume that households in the quantitative model have perfect foresight due to the binding computational constraint of solving the model under uncertainty.

As is common in the discrete choice literature, we assume the idiosyncratic shock $\epsilon_{i,t}^{s}$ is an independently and identically distributed Type-I Extreme Value random variable with zero mean. Defining $V_{n,t}^{k}\equiv\mathbb{E}_{\epsilon}\left[v_{n,t}^{k}\right]$ and taking an expectation with respect to ϵ over equation (4) yields:

$$V_{n,t}^{k}=U\left(C_{n,t}^{k},B_{n,t}\right)+\nu\log\left(\sum_{i=1}^{N}\sum_{s=0}^{K}\exp\left[\left(\beta V_{i,t+1}^{s}-\mu_{ni}^{ks}\right)/\nu\right]\right). \tag{5}$$

The Type-I Extreme Value assumption on the idiosyncratic shocks also delivers the following closed-form expression for the share of households migrating from (n,k) to (i,s):

$$\pi_{ni,t}^{ks}=\frac{\exp\left[\left(\beta V_{i,t+1}^{s}-\mu_{ni}^{ks}\right)/\nu\right]}{\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta V_{l,t+1}^{h}-\mu_{nl}^{kh}\right)/\nu\right]}. \tag{6}$$

Given the migration shares in equation (6), the evolution of the labor distribution across markets over time $\left\{L_{n,t}^{k}\right\}_{n=1,k=0}^{N,K}$ is captured by the following equation for each time t:

$$L_{n,t+1}^{k}=\sum_{i=0}^{N}\sum_{s=0}^{K}\pi_{in,t}^{sk}L_{i,t}^{s}. \tag{7}$$

Since households choose where to relocate to at the end of each period, labor supply at the beginning of any period t is already determined by previous actions. With this timing, we now proceed to describe the static production side of the model.

1.2 Production And Labor Demand

At each time t, producers in region n and industry k produce output using a two-tier Cobb-Douglas constant returns to scale technology:

$$q_{n,t}^{k} = z_{n,t}^{k} \left[(H_n^k)^{\psi^k} (L_{n,t}^k)^{1-\psi^k} \right]^{\gamma_n^k} \prod_{s=1}^{K} \left(M_{n,t}^{ks} \right)^{\gamma_n^{ks}} \tag{8}$$

where H_n^k is local structures (immobile and non-accumulating capital), $L_{n,t}^k$ is labor, and $M_{n,t}^{ks}$ is intermediate inputs produced in industry s in the same region. ψ^k is the share of local structures in value added, γ_n^k is the share of value added, and γ_n^{ks} is the share of intermediate inputs produced in sector s in the same region, with $\gamma_n^k + \sum_{s=1}^{K} \gamma_n^{ks} = 1$. The unit price of an input bundle is given by:

$$x_{n,t}^{k} = \kappa_n^k \left[\left(r_{n,t}^k \right)^{\psi^k} \left(w_{n,t}^k \right)^{1-\psi^k} \right]^{\gamma_n^k} \prod_{s=1}^{K} \left(P_{n,t}^{s} \right)^{\gamma_n^{ks}} \tag{9}$$

where κ_n^k is a constant, $r_{n,t}^k$ is the rental rate of local structures, and $P_{n,t}^k$ is also the price of the local industry aggregate of varieties used as intermediate inputs in production.[13]

Given their exogenous productivity $z_n^k(\xi)$, a producer of variety ξ in market (n,k) produces $q_{n,t}^k(\xi)$ units of output. As in EK, we assume that for all regions n, industries k, and their varieties ξ, $z_n^k(\xi)$ is a random variable drawn independently for each triplet (n,k,ξ) from a Fréchet distribution $F_{n,t}^k(z)$ such that:

$$F_{n,t}^k(z) = \exp\left[-Z_{n,t}^k (z)^{-\theta^k} \right]. \tag{10}$$

The shape parameter θ^k measures the strength of intra-industry heterogeneity and captures the extent to which there are idiosyncratic differences in technological know-how across varieties. The scale parameter $Z_{n,t}^k > 0$ represents the time-varying fundamental productivity of market (n,k), and embodies factors such as climate, infrastructure, and institutions that affect the productivity of all producers at time t in a given region and industry.

We assume that $Z_{n,t}^k$ is multiplicatively separable in a vector of weather variables $\mathbf{T_{n,t}}$:

$$Z_{n,t}^k = \bar{Z}_{n,t}^k \exp\left(g(\mathbf{T_{n,t}}; \zeta_{\mathbf{Z}}^{\mathbf{k}}) \right) \tag{11}$$

where $\bar{Z}_{n,t}$ is *base productivity* and captures exogenous non-weather industry-specific deter-

[13]The latter arises from the typical assumption that both consumers and producers of intermediate inputs use the same CES aggregator over industry varieties.

minants of fundamental productivity, $\mathbf{T}_{n,t}$ is a vector of weather variables in region n in year t as explained in the household problem, $g(\mathbf{T}_{n,t};\zeta_{\mathbf{Z}}^{k})$ is a flexible weather response function, and $\zeta_{\mathbf{Z}}^{\mathbf{k}}$ is a set of parameters to be estimated that govern how weather affects local industry-specific productivity. We assume that non-weather base productivity $\bar{Z}_{n,t}^{k}$ grows at an exogenous rate of $\wp_{n,t}^{k}$.

1.3 Trade and Market Clearing

Trade costs are of the standard iceberg type, so that delivering one unit of any good in industry k from region i to region n at time t requires shipping $\tau_{ni,t}^{k} \geq 1$ units of the good, with $\tau_{nn,t}^{k} = 1$ for all n and k, and $\tau_{ni,t}^{k} \leq \tau_{nl,t}^{k}\tau_{li,t}^{k}$ for all i, n, l and k (triangular inequality). The price of each industry k variety ξ in region n is the minimum unit cost across all regions:

$$p_{n,t}^{k}\left(\xi\right) = \min_{1\leq i\leq N}\left\{\frac{\tau_{ni,t}^{k}x_{i,t}^{k}}{z_{i,t}^{k}(\xi)}\right\}.$$

Let $X_{ni,t}^{k}$ denote the time t total expenditure of region n on goods from region i in industry k, let $X_{n,t}^{k} \equiv \sum_{l=1}^{N} X_{nl,t}^{k}$ denote the total expenditures of region n in industry k, and let $\lambda_{ni,t}^{k} \equiv X_{ni,t}^{k}/X_{n,t}^{k}$ denote industry-level bilateral trade shares. Following the procedure in EK yields the following expression for trade shares:

$$\lambda_{ni,t}^{k} = \frac{Z_{i,t}^{k}\left(x_{i,t}^{k}\tau_{ni,t}^{k}\right)^{-\theta^{k}}}{\sum_{l} Z_{l,t}^{k}\left(x_{l,t}^{k}\tau_{nl,t}^{k}\right)^{-\theta^{k}}}. \tag{12}$$

In turn, the price index for industry k in region n is:

$$P_{n,t}^{k} = \Gamma^{k}\left(\sum_{l=1}^{N} Z_{l,t}^{k}\left(x_{l,t}^{k}\tau_{nl,t}^{k}\right)^{-\theta^{k}}\right)^{-1/\theta^{k}} \tag{13}$$

where Γ^{k} is a constant, and $1+\theta^{k} > \sigma^{k}$ guaranteeing a well-defined price index.[14]

Finally, our model also allows for trade imbalances. In each location n, there is a unit mass of immobile local capitalists that own the immobile local structures. The capitalists rent the local structures to producers at rate $r_{n,t}^{k}$, and use the revenues to invest in a global portfolio. They in turn receive a constant share ι_{n} from the global portfolio, with $\sum_{n=1}^{N}\iota_{n} = 1$. Capitalists spend this income across local goods like households, given by equation (2). Time-varying trade imbalances are thus given by the difference between the time-varying

[14]Specifically, $\Gamma^{k} \equiv \Gamma\left(\frac{1-\sigma^{k}+\theta^{k}}{\theta^{k}}\right)^{\frac{1}{1-\sigma^{k}}}$, where Γ is the Gamma function.

rents capitalists collect, and the income they receive from investing in the global portfolio, i.e. $\sum_{k=1}^{K} r_{n,t}^k H_n^k - \iota_n \chi_t$, where $\chi_t = \sum_{i=1}^{N}\sum_{k=1}^{K} r_{n,t}^k H_n^k$ are the total revenues in the global portfolio at time t.

In each market (n,k), goods market clearing implies that total expenditures is equal to total income:

$$X_{n,t}^k = \sum_{s=1}^{K} \gamma_n^{sk} \sum_{i=1}^{N} \lambda_{in,t}^k X_{i,t}^k + \alpha^k \sum_{k=1}^{K} w_{n,t}^k L_{n,t}^k + \alpha^k \iota_n \chi_t. \tag{14}$$

Total income has three components. The first term on the right-hand side is the total expenditure of firms in all markets on goods produced in market (n,k), the second term is the total income of households residing and working in market (n,k), and the third term is the total income of local capitalists in market (n,k). Additionally, labor market clearing in market (n,k) means that labor income equals the labor share of expenditures on (n,k) output:

$$w_{n,t}^k L_{n,t}^k = \gamma_n^k (1-\psi^k) \sum_{i=1}^{N} \lambda_{in,t}^k X_{i,t}^k, \tag{15}$$

and market clearing for local structures means that rental income equals the capitalist share of expenditures on (n,k) output:

$$r_{n,t}^k H_n^k = \gamma_n^k \psi^k \sum_{i=1}^{N} \lambda_{in,t}^k X_{i,t}^k. \tag{16}$$

1.4 Equilibrium

Given the distribution of labor across markets $L_t \equiv \left\{L_{n,t}^k\right\}_{n=1,k=0}^{N,K}$, local structures $H \equiv \{H_n^k\}_{n=1,k=0}^{N,K}$, location-industry fundamental productivities $Z_t \equiv \left\{Z_{n,t}^k\right\}_{n=1,k=1}^{N,K}$, industry-level bilateral trade costs $\tau_t \equiv \left\{\tau_{ni,t}^k\right\}_{n=1,i=1,k=0}^{N,N,K}$, migration costs $\mu \equiv \left\{\mu_{ni}^{ks}\right\}_{n=1,i=1,k=0,s=0}^{N,N,K,K}$ and home production $b = \{b_n\}_{n=1}^{N}$, we define a time-t **momentary equilibrium** as a vector of wages $w_t \equiv \left\{w_{n,t}^k\right\}_{n=1,k=1}^{N,K}$ satisfying equilibrium conditions (9) and (12) – (16) of the static sub-problem. This equilibrium is the solution to a static multi-regional and multi-industry trade model. Let $\pi_t \equiv \left\{\pi_{ni,t}^{ks}\right\}_{n=1,i=1,k=0,s=0}^{N,N,K,K}$, $B_t \equiv \{B_{n,t}\}_{n=1}^{N}$ and $V_t \equiv \left\{V_{n,t}^k\right\}_{n=1,k=0}^{N,K}$ be migration shares, amenities, and lifetime utilities respectively. Given an initial allocation of labor L_0, time-invariant exogenous fundamentals μ, b and H, and a path of time-varying exogenous fundamentals $\{B_t, Z_t, \tau_t\}_{t=0}^{\infty}$, we define a **sequential competitive equilibrium** as a sequence of $\{L_t, \pi_t, V_t, w_t\}_{t=0}^{\infty}$ that solves equilibrium conditions (5) – (7) and the temporary equilibrium at each time t. Finally, we define a **stationary equilibrium** as a sequential competitive equilibrium such that the sequence $\{L_t, \pi_t, V_t, w_t\}_{t=0}^{\infty}$ is constant for every t.

2 From Theory to Data: Linking Microeconometrics and Macro Simulation

Here we describe how we go from the theoretical model to the quantitative results. First, we show how we construct our temperature response functions. Second, we show how we use the dynamic spatial equilibrium conditions of our model to estimate the effects of weather on productivity and amenities. These estimating equations capture the direct impact of weather on the objects of interest without any confounding from spatial spillovers or forward-looking behaviors that are represented by the model. Third, we define the metric we use to compute the welfare impacts of climate change. Fourth, we describe how we simulate the model and decompose the impacts of climate change.

2.1 Constructing the Response Functions

In our estimation and quantitative results we focus on the distribution of daily average temperature within each year t. We construct our temperature response function by starting with the distribution of intra-daily temperature in each region-year from the historical temperature record. We then discretize the distribution within each region-year into bins of 1°C, where each bin captures the number of days in year t – where a bin can have fractions of a day – that region n's daily temperature lies in that bin. The values across all 1°C bins then sum up to the number of days in year t, and the total annual effect on our outcomes of interest is the sum of the individual daily effects across the bins. We winsorize the distribution so there is a lower exposure bin containing all daily temperatures ≤-15°C and an upper exposure bin containing daily temperatures ≥50°C. Similar to Schlenker and Roberts (2009), we evaluate the effect of exposure to an additional day in each bin using a third-degree orthogonal polynomial in order to allow for flexible and asymmetric responses to hot versus cold temperatures. An alternative way to describe this is we are using a third-degree approximation to ensure a smooth relationship between our temperature bins rather than estimating 66 separate coefficients. The level of $g(\mathbf{T_{n,t}}; \zeta_{\mathbf{Z}}^{\mathbf{k}})$ and $f(\mathbf{T_{n,t}}; \zeta_{\mathbf{B}})$ at each bin tells us the effect of an additional day of the year at that temperature on productivity and amenities. Details on the data required for estimating our temperature response functions are presented in Appendix C.1.

2.2 Trade Flows Identify Effects on Local Productivity

To estimate the direct effect of temperature on local productivity, we use the equilibrium conditions of the model governing bilateral trade flows. Appendix D.1 shows how we can use equations (12) and (13) to obtain a new equilibrium condition:

$$\log\left(\frac{X^k_{ni,t}}{X^k_{nn,t}}\right) = \left[g(\mathbf{T}_{i,t};\zeta^k_{\mathbf{Z}}) - g(\mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}})\right] + \log\left(\frac{\bar{Z}^k_{i,t}}{\bar{Z}^k_{n,t}}\right) - \theta^k \log\left(\tau^k_{ni,t}\right) - \theta^k \log\left(\frac{x^k_{i,t}}{x^k_{n,t}}\right). \tag{17}$$

In equilibrium, the ratio of expenditures on products from another region i relative to own expenditures must be equal to three components. The first component consists of the first two terms which correspond to the difference in productivity levels between i and n. This component itself is determined by differences in the non-weather component of fundamental productivity, and differences in the effect of local temperature on productivity across n and i. If i more productive than n then n will tend to import more from i relative to purchasing its own goods. The second component is iceberg trade costs. This is relative to changes in own-trade costs $\tau^k_{nn,t}$, however own-trade costs are defined to be 1. If trade costs are higher, then imports from i relative to own expenditures will be lower. The last component is the relative unit price of an input bundle. If input costs in i are higher than in n, the price of goods from i will be higher as well. This decreases imports relative to own expenditures. Input costs are not directly observed in the data as they are an aggregation of wages, rental prices, and prices of intermediates which are ultimately determined by trade costs and factor prices in other markets.

We use the following model as our main specification for estimating the response function:

$$\log\left(\frac{X^k_{ni,t}}{X^k_{nn,t}}\right) = \left[g(\mathbf{T}_{i,t};\zeta^k_{\mathbf{Z}}) - g(\mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}})\right] - \theta^k \log\left(\tau^k_{ni,t}\right) + \zeta_{\mathbf{X}}\mathbf{X_t} + \rho^k_t + \varphi^k_{ni} + \varepsilon^k_{ni,t}. \tag{18}$$

We calibrate θ^k to the values estimated in Caliendo and Parro (2015) in order to focus on the estimation of ζ^k_Z. We proxy for trade costs $\log\left(\tau^k_{ni,t}\right)$ using time-varying data on tariffs, and we proxy for input costs by controlling for wages and rental rates of the importer and exporter in $\mathbf{X_t}$. $\zeta^{\mathbf{k}}_{\mathbf{Z}}$ is the vector of coefficients we will estimate that determine how productivity responds to temperature. We estimate the parameters of the model using Poisson Pseudo Maximum Likelihood (PPML) following the convention in the empirical trade literature.[15]

The remaining piece of equation (17) is the difference in base productivity across importer and exporter. Our empirical specification also includes importer-exporter-industry fixed effects φ^k_{ni} and industry-year fixed effects ρ^k_t to control for components of unobserved base productivity that may be correlated with temperature. $\varepsilon^k_{ni,t}$ is the error term and captures the remaining variation in base productivity within an importer-exporter-industry triplet

[15]Silva and Tenreyro (2006) demonstrates how estimating the log-linear OLS equation can lead to biased estimates because the fundamental equation is multiplicative because of a Jensen's inequality argument.

over time. We cluster our standard errors two ways at the importer and exporter level to account for autocorrelation and within-country correlation in errors across trading partners or industries. In our empirical application we estimate both the average response function across all industries, $\zeta_{\mathbf{Z}}$, as well as sector-specific response functions, $\zeta^k_{\mathbf{Z}}$. The sector-specific response functions come from a single regression where we interact the response function g with a set of three sector dummy variables: agriculture, manufacturing (including mining and construction), and services.

2.3 Migration Shares Identify Effects on Local Amenities

To estimate the effect of temperature on amenities, we exploit variation in migration flows, wages, and daily temperature along with equation (5). Appendix D.2 shows how this equation can be converted into an Euler equation that governs the optimal dynamic migration decisions for households, and then how further substitutions deliver an equation linear in economic observables and functions of temperature:

$$\begin{aligned}\log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) &= \frac{\beta}{\nu}\left[f(\mathbf{T_{i,t+1}};\zeta_{\mathbf{B}}) - f(\mathbf{T_{n,t+1}};\zeta_{\mathbf{B}})\right] + \frac{\beta}{\nu}\log\left(\frac{\bar{B}_{i,t+1}}{\bar{B}_{n,t+1}}\right) \\ &\quad + \frac{\beta}{\nu}\log\left(\frac{\omega^s_{i,t+1}}{\omega^k_{n,t+1}}\right) + \frac{\beta-1}{\nu}\mu^{ks}_{ni} + \beta\log\left(\frac{\pi^{ks}_{ni,t+1}}{\pi^{ss}_{ii,t+1}}\right) + \varepsilon^{ks}_{ni,t}.\end{aligned} \tag{19}$$

Equation (19) must hold in dynamic spatial equilibrium. The left hand side is the ratio of households who move to (i,s) versus stay in the original market (n,k) at the end of time t.[16] In equilibrium, this ratio is equal to the sum of four components: three components of the one period ahead flow payoff, and one component corresponding to the continuation value.

The first is the one period ahead differences in amenities which is captured by the terms on the first line. If amenities are better in i than n at time $t+1$, households are more likely to migrate to i from n because their time $t+1$ payoff will be higher in i, all else equal. The total difference in amenities consists of differences in temperature impacts on amenities and differences in unobserved non-temperature components of amenities.

The second component is the one period ahead difference in wages. Households will tend to move to the markets with higher real wages in the next period, all else equal.

The third component is the unobserved moving cost, the first term on the second line. Since $\beta-1$ is negative, greater moving costs reduce the likelihood of households out-migrating relative to staying.

[16] This term is equal to the expected net benefits of moving from (n,k) to (i,s) scaled by the migration elasticity.

The final component is the ratio of households who migrate from n to i relative to those who stay in i. This captures differences in the expected future welfare from starting $t+2$ in market (n,k) relative to market (i,s). Appendix D.2 shows that this is composed of two parts, the difference in the value of continuing beyond $t+2$ in either n or i, and the difference in option value of being able to move from n or i. This additional option value is why the denominator is the staying-share of the destination rather than origin like the left hand side. This term acts as a sufficient statistic for future welfare beyond $t+1$ and absorbs the impact of expectations about future temperatures, real wages, and amenities. Conditioning on this term is what allows us to isolate effects of temperature on flow utility in a model with forward-looking behavior.

Similar to the productivity regression, we calibrate β to an annual rate of 0.98, and $\nu = 2.02$ following CDP and Artuc et al. (2010) in order to focus on the estimation of $\zeta_{\mathbf{B}}$. After pinning down β and ν, our specification for estimating the effect of temperature on amenities is:

$$\log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) = \frac{\beta}{\nu}\left[f(\mathbf{T_{i,t+1}};\zeta_{\mathbf{B}}) - f(\mathbf{T_{n,t+1}};\zeta_{\mathbf{B}})\right] + \frac{\beta}{\nu}\log\left(\frac{\omega^{s}_{i,t+1}}{\omega^{k}_{n,t+1}}\right) + \beta\log\left(\frac{\pi^{ks}_{ni,t+1}}{\pi^{ss}_{ii,t+1}}\right) + \delta^k_t + \varphi^k_{ni} + \varepsilon^{ks}_{ni,t} \tag{20}$$

where we set $s = k$ since $\zeta_{\mathbf{B}}$ is only identified off migration variation[17]. φ^k_{ni} is an origin-destination-industry effect and δ^k_t is an industry-year effect. These fixed effects are included to fully capture the unobserved moving costs, and non-temperature components of local amenities. $f(\mathbf{T_{i,t+1}};\zeta_{\mathbf{B}})$ is generated in the same way as $g(\mathbf{T_{i,t+1}};\zeta_{\mathbf{Z}})$ was for productivity effects using binned daily temperatures and third-order orthogonal polynomials. We estimate $\zeta_{\mathbf{B}}$ using PPML. We cluster our standard errors two ways at the origin and destination to account for correlation in shocks across origins for each destination, and across destinations for each origin. For estimating the amenity response, we use cross-state US migration data since bilateral cross-country migration data is not widely available. Section G.1 in the appendix contains robustness checks for the productivity and amenities response functions, including changing the set of fixed effects, parameter values, and the order of polynomials

[17]This amenities estimation approach highlights the importance of labor markets in valuing amenities. Changes in environmental variables such as temperature can affect local productivity in addition to local amenities, inducing sorting on real wages. Regressing migration flows – or other common variables such as housing prices – confound the amenities effect with the productivity effect if real wages are not included as a control. Additional variables of interest, such as local ozone pollution, could be included in the model if we wanted to disentangle the direct value of temperature versus its indirect value through the positive effect of temperature on ozone concentrations.

or splines.

2.4 Model-Consistent Productivity and Amenity Response Functions

We now present the estimated response functions. The left side of Figure 2 shows the average productivity response function across all industries from equation (18). In the aggregate, productivity peaks at 18°C, cold temperatures slightly reduce productivity while hot temperatures substantially reduce productivity. If a single day of the year at 18°C is replaced by a day 36°C, productivity declines by 0.9 percentage points.

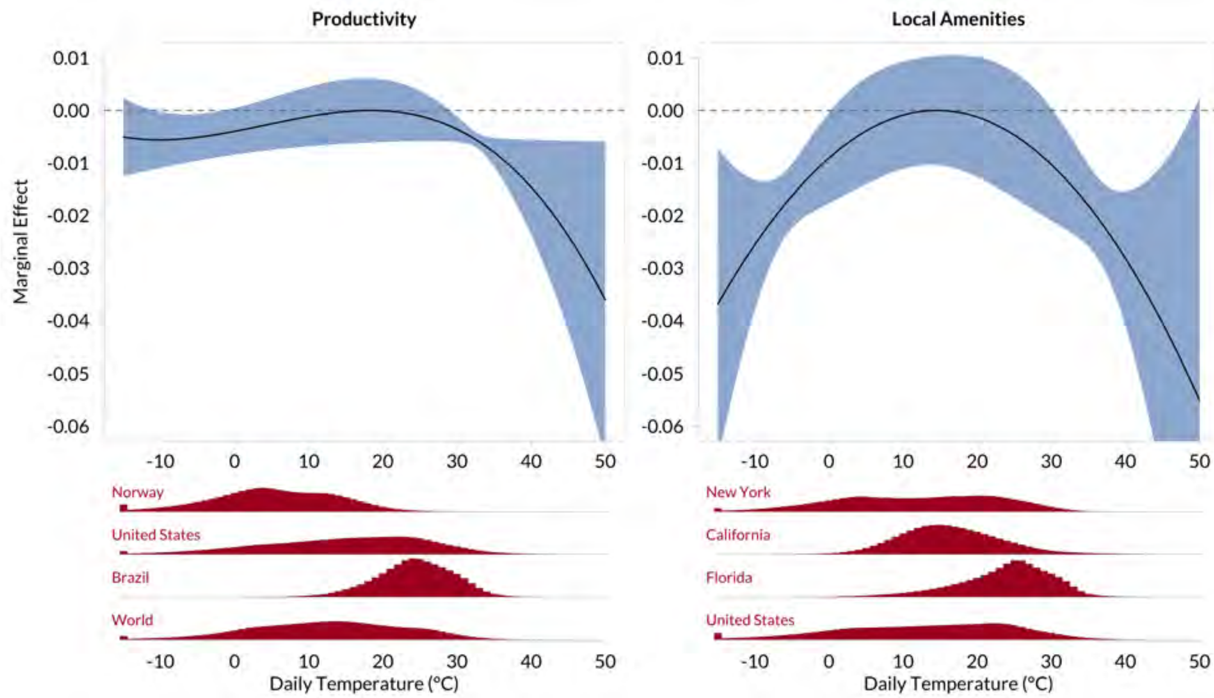
The aggregate productivity response function in Figure 2 masks significant cross-sectoral heterogeneity. Figure 3 presents sector-specific temperature response function for three sectors: agriculture, manufacturing, and services. The industries composing these sectors are listed in Appendix A. Consistent with the prior literature, agriculture has a significant non-linear response to daily temperature and hot temperatures are extremely damaging (Schlenker and Roberts, 2009). Also consistent with prior evidence, manufacturing is sensitive to extreme heat (Zhang et al., 2018), albeit to a lesser extent than agriculture. Finally, we find that the services sector is only marginally affected by extreme temperatures.

The right side of Figure 2 shows the amenity response function estimated from equation (20). The amenity response function is inverse-U-shaped and peaks at 15°C: unlike productivity households do not like cold temperatures. Replacing one day at 15°C with one at 33°C reduces welfare by 1.1 percentage points.

To get a sense of the size of our estimates, we compare our findings to the existing literature measuring impacts of temperature on output, income, and amenities. Burke et al. (2015) find that global GDP growth peaks at an annual average temperature of 13°C, and that annual growth would be 8 percentage points lower if annual average temperature is 10°C warmer or cooler. Deryugina and Hsiang (2017) show that in the United States, income per capita is inverse-U shaped in daily temperature, maximized at 15°C, with income declines of .05% for each day above 25°C. In approaches not allowing for non-linear effects, Colacito et al. (2018) find that a 1°C increase in average summer temperature reduces GDP growth in the United States by over 0.3 percentage points, while Dell et al. (2012) find that a 1°C increase in annual average temperature reduces growth by 1.4 percentage points in poor countries. In one of the few comparable papers on amenities, Albouy et al. (2016) find Americans' preferred temperature is around 18°C and project future annual welfare losses of 1%–4% from worsening amenities.

Additionally, we compare our temperature response functions with alternative partial

Figure 2: The effect of daily temperature on local productivity and amenities.



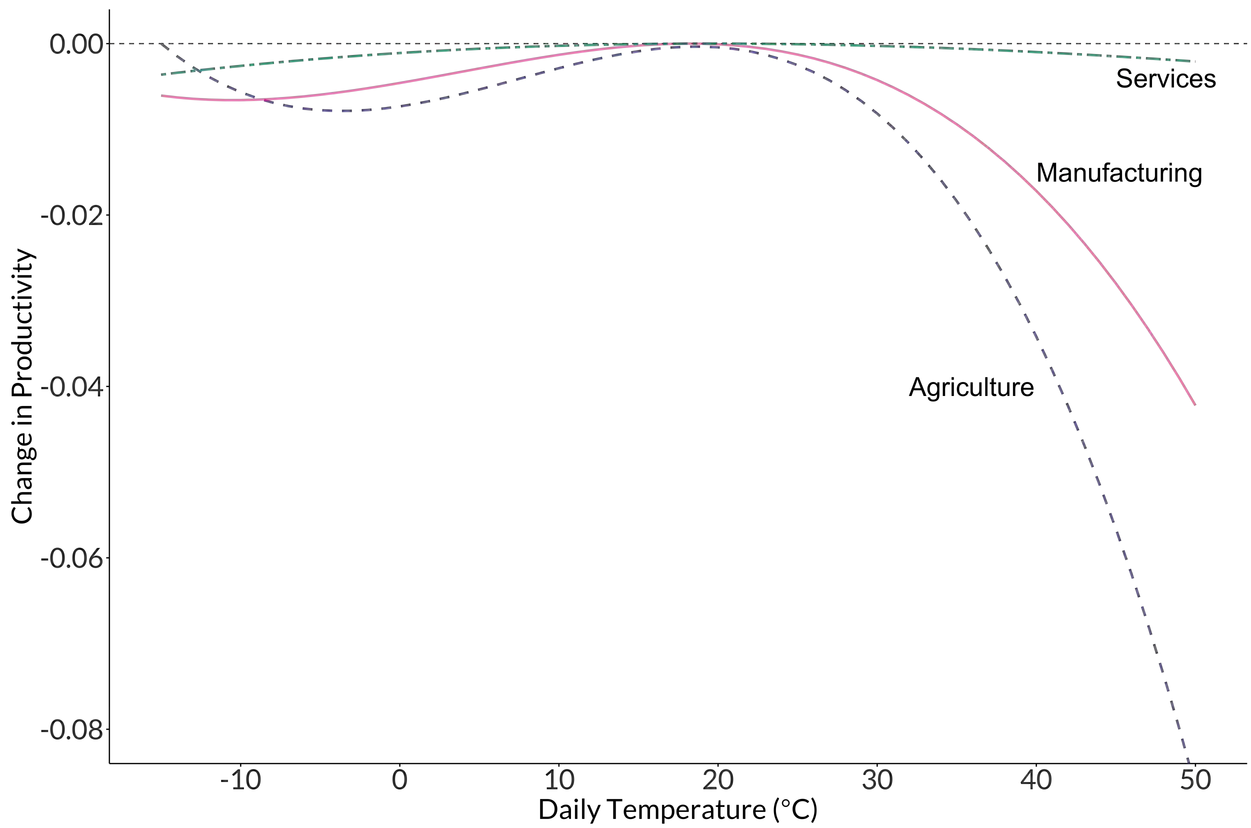
The response functions are constructed using a third-degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are winsorized at -15°C and 50°C. The shaded areas denote the 95% confidence intervals. The peak of the response functions have been normalized to zero for plotting.
Left: The response function is from estimating equation (18) and reflects the average effect across all industries. Standard errors are clustered two ways at the exporter country and importer country. Figure 3 shows effects separately by industry.
Right: The response function is from estimating equation (20). Standard errors are clustered two ways at the origin state and destination state.
Bottom: The histograms show the distribution of daily temperature for a set of locations from 2000–2014.

equilibrium reduced form approaches used in the literature in Appendix D.3. We provide intuition and empirically show how the effects of temperature on productivity are biased toward zero when not accounting for spatial linkages across observational units in the empirical approach while temperature is positively spatially correlated. We also show that not accounting for households' forward-looking actions will lead us to underestimate households' preferred temperature.

2.5 Welfare Definition

We now define our measure of welfare. We define our welfare measure as the equivalent variation in consumption for households in market (n, k) in the initial period. Let primes denote variables under the counterfactual climate, the equivalent variation is the value of δ_n^k

Figure 3: The direct effect of temperature on productivity by industry.



Note: The response functions are constructed using a third-degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The shaded areas denote the 95% confidence intervals. The response functions are from estimating equation (18) but where g is interacted with a set of sector dummy variables for agriculture, manufacturing, and services. The peak of the response functions have been normalized to zero for plotting.

such that:

$$V_{n,0}^{k}{}' = V_{n,0}^{k} + \sum_{t=0}^{\infty} \beta^t \log\left(\delta_n^k\right) = \sum_{t=0}^{\infty} \beta^t \log\left(B_{n,t} \frac{C_{n,t}^k}{\left(\pi_{nn,t}^{kk}\right)^{\nu}} \delta_n^k\right).$$

where welfare under the counterfactual climate is:

$$V_{n,0}^{k}{}' = \sum_{t=0}^{\infty} \beta^t \log\left(B_{n,t}' \frac{C_{n,t}^{k}{}'}{\left(\pi_{nn,t}^{kk}{}'\right)^{\nu}}\right)$$

Let dots denote time differences: $\dot{x}_{t+1} = \frac{x_{t+1}}{x_t}$, and hats denote time differences for the counterfactual relative to the factual outcome: $\hat{x}_{t+1} = \frac{\dot{x}_{t+1}'}{\dot{x}_{t+1}}$. We call the hat variables relative time differences. The consumption-equivalent change in welfare can then be computed using relative time difference variables:

$$\log\left(\delta_n^k\right) = \sum_{t=1}^{\infty} \beta^l \log\left(\widehat{B_{n,t}} \frac{\widehat{C_{n,t}^k}}{\left(\widehat{\pi_{nn,t}^{kk}}\right)^{\nu}}\right)$$
$$= \sum_{t=1}^{\infty} \beta^t \left[\underbrace{\log \widehat{B_{n,t}}}_{\substack{\text{direct climate}\\ \text{impact on}\\ \text{amenities}}} \underbrace{- \nu \log \widehat{\pi_{nn,t}^{kk}}}_{\substack{\text{changes in}\\ \text{option value}}} + \underbrace{\log \widehat{w_{n,t}^k} - \log \widehat{P_{n,t}}}_{\text{changes in real wages}}\right]. \tag{21}$$

We provide a more detailed decomposition of welfare in Appendix E.1 to build more intuition on the different mechanisms through which climate impacts the economy. We show how this welfare computation needs to be modified for the simulations when we hold migration fixed to the no climate change scenario (as described below) in Appendix E.2.

2.6 Simulating and Decomposing the Impacts of Climate Change

We simulate our full model using the dynamic hat algebra technique introduced in CDP. In the model, we simulate the economy forward from 2015–2100 using the projected annual distribution of daily temperature averaged across 17 global climate models (GCMs) under the Representative Concentration Pathways (RCP) 4.5 scenario. This scenario generates end of century global average warming of approximately 2.5°C–3°C. We then compute welfare and other economic outcomes relative to a counterfactual where amenities and productivity are held fixed which implies that the distribution of daily temperature is held fixed to its initial level. The GCMs we use are listed in Appendix B.1.

Our simulations hold trade costs and moving costs fixed to their 2015 levels, which are identified from data on migration shares, trade shares, and bilateral expenditures. We assume that the non-temperature component of amenities, $\bar{B}_{n,t}$ also remains constant at its 2015 level, however we do not need to identify this term in order to simulate our model. We allow base productivity growth $\wp_{n,t}^k$ to change exogenously over time. We generate productivity growth paths using data on productivity from the Shared Socioeconomic Pathway 2 (SSP2) scenario, the economic growth scenario that corresponds to the RCP 4.5 emission scenario. Appendix B.3 plots these baseline productivity growth trajectories.

After presenting the baseline results, we decompose the effects of different economic attributes and adaptation mechanisms. We consider five economic channels: the transmission of climate shocks through input-output linkages, local amenities, forward-looking household behavior, sectoral heterogeneity in the productivity effects of temperature, and the representation of daily temperature versus only using annual means. To identify the role of adaptation through trade and labor reallocation, we first simulate the model under the no climate change counterfactual, then run the RCP 4.5 climate change simulation holding the trajectory of trade shares or migration and industry switching shares fixed to their equilibrium trajectories from the no climate change simulation. This exercise still allows these margins to adjust over time, just not in response to changes in climate. We present this formally by way of a series of propositions in Appendix F. Of note, are Proposition 5 and 6 in Appendix F.3 which isolate the role of trade and migration responses to climate shocks, but the propositions apply more generally to any economic shocks to fundamentals. Appendix C.2 describes the data required for the simulations.

3 Quantitative Results

Figure 4 shows the change in the distribution of within-year daily temperature for each state from 2015–2100, averaged across all 17 GCMs.[18] Each graph shows the state's increase in number of days per year in each temperature bin. From the figure we can see that Alaska experiences a significant decrease in extreme cold days that are offset by more moderate days near the peak for productivity and amenities. Maine, another cold state, also experiences a decline in extreme cold days, however these tend to be offset by hot days rather than moderate days. States in the Pacific Northwest have less stark changes in their temperature distributions, while states in the South trade cool and moderate days for additional extremely hot days above 30°C.

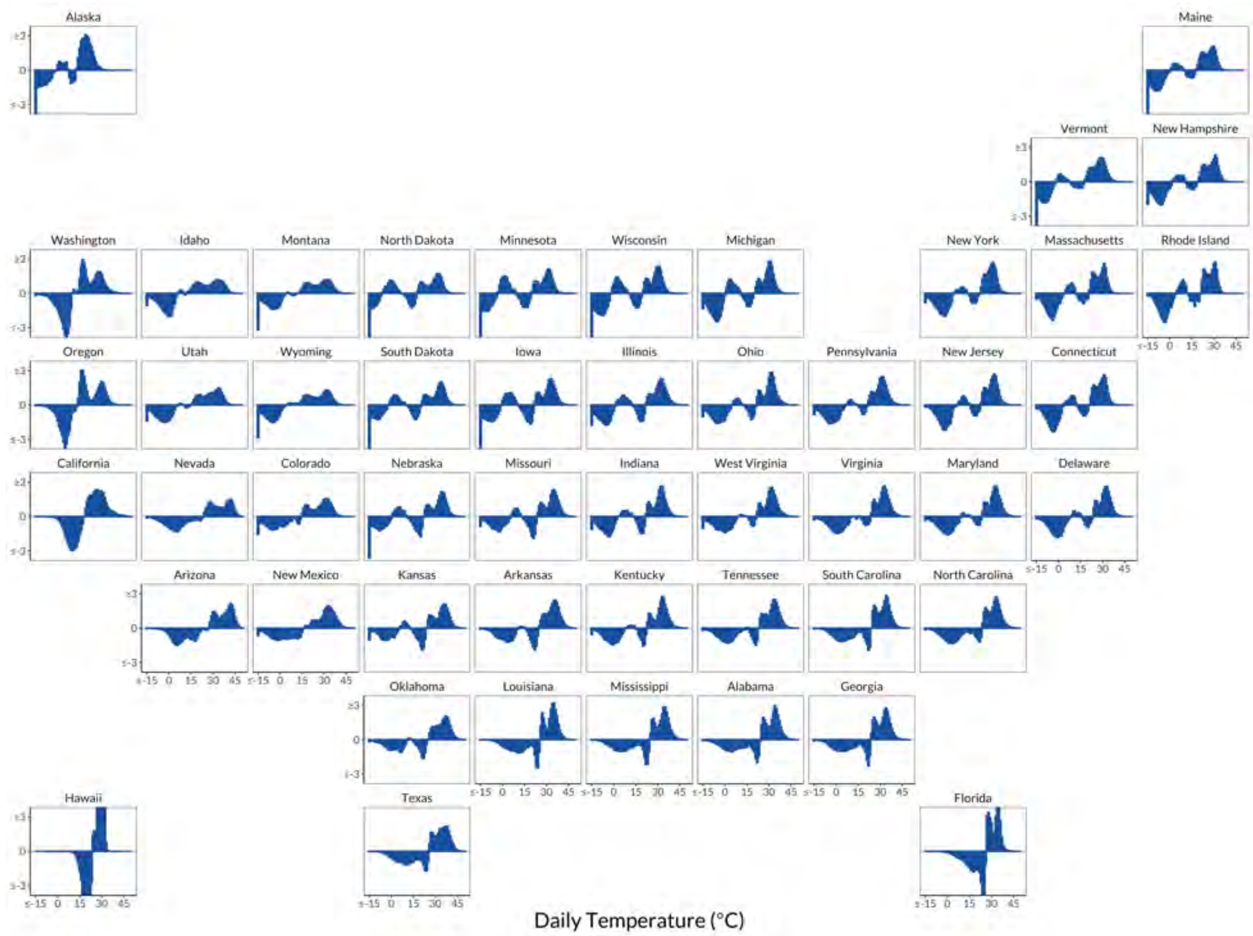
3.1 Impacts of Climate Change in the Basic Model

Our first set of welfare results are in Figure 5 which depicts US welfare impacts of future climate change. The top row presents results from what we call our *basic model*. This is a stripped down version of the full model presented in Section 1 with no impacts on amenities, the common response function across all industries in the left panel of Figure 2, no input-output loops, myopic households, temperature represented as annual means instead of a set of daily means, and no adaptation through trade or labor reallocation.[19] What this does is effectively shut down all general equilibrium effects across space and industries, and removes our detailed representation of the climate and its impacts. This model serves as a benchmark that we use to generate similar results to reduced form, partial equilibrium

[18] Figure B.1 shows the same distributions but for each region in our model.

[19] As described above, we shut down trade and labor reallocation by holding the trajectories of trade shares and migration shares to their counterfactual, no climate change trajectories.

Figure 4: Change in within-year daily temperature distributions: 2015–2100.



Note: Each plot shows the state-specific change in the number of days in each 1°C temperature bin from the first to last year of the RCP 4.5 climate scenario, averaged over 17 GCMs. Positive numbers denote increases in days at that temperature, negative numbers denote decreases. The temperature distributions are winsorized at -15°C and 50°C.

production function-based approaches that estimate the effect of temperature on GDP and then simulate forward in time without accounting for general equilibrium and non-market impacts.

The top left panel of Figure 5 plots the welfare change for the incumbent households in each state. In the basic model, climate change will have heterogeneous effects across the United States. Northern states like North Dakota or Vermont are better off by up to 7%, while the South and Hawaii suffer losses of up to 5%. In population average terms, the basic model predicts US welfare will increase by a population-weighted average of 1.9%.

The top right panel shows welfare results for all other countries. Countries at high latitudes like Finland or Canada tend to have welfare improvements, while countries near the equator like India or Brazil have welfare losses. In population average terms, this model predicts the world will suffer a loss of 4.9% because most people live in regions of the world that are worse off, despite most regions represented in our model being better off. Our basic model generates similar distributional results to the previous literature estimating global welfare impacts (e.g. Burke et al., 2015; Cruz and Rossi-Hansberg, 2021).[20]

3.2 The Role of Different Economic Channels

With results from the benchmark basic model in hand, we now build up to what we call our *full model*, which includes amenities impacts as in the right panel of Figure 2, heterogeneous sectoral responses to temperature as in Figure 3, input-output loops, forward-looking households, and daily temperature. Before presenting the full welfare results, we first compute the welfare impact of each model attribute by simulating the basic model plus one – or all – of these attributes, and then comparing the result to the basic model US welfare impacts of 1.9% and global welfare impact of -4.9%. We report the results for both cases with adjustments to climate change through trade, migration, or industry switching, and those without.

To formalize this, recall that δ_n^k denotes our consumption-equivalent change in welfare for market (n, k) from equation (21). Let δ be the population-weighted average of all δ_n^k's in our basic model results shown in the top row of Figure 5. Let δ^{+H} denote the welfare effect of climate change in the basic model but with structural attribute H added where H may be amenities impacts, input-output loops, etc. Our measure of change in welfare from properly accounting for structural attribute H is:

$$\Delta^H := \delta^{+H} - \delta.$$

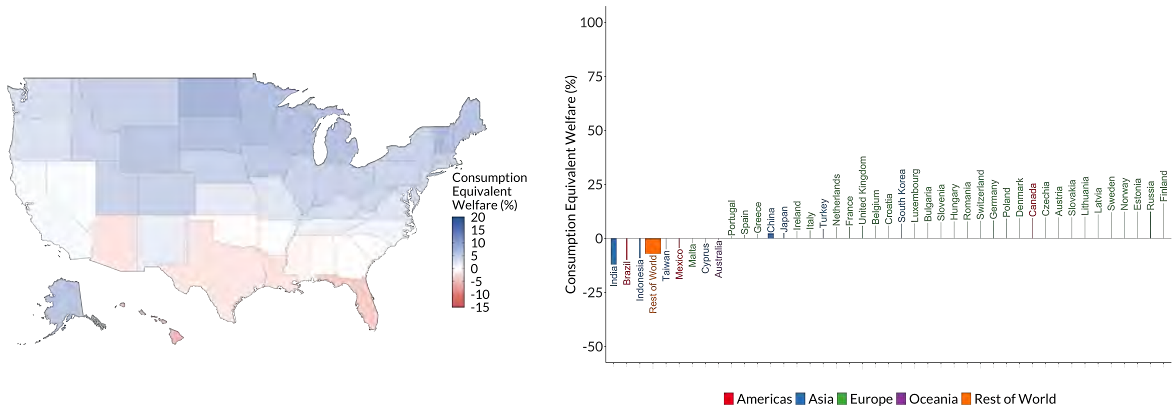
We present estimates of Δ^H in Table 1 on model attributes not directly related to trade, migration, or industry switching. The first row reports the level of welfare in the US and for the entire world in the basic model. The remaining rows in Table 1 report Δ^H for a different attribute H. The first two columns show US results with and without adaptation adjustments through trade and the labor market, while the last two columns are the same but for the world.

The second row shows the welfare effect of input-output linkages introduced by intermediates in production. Input-output linkages tend to offset some of the impacts of climate change, reducing gains in the United States and mitigating losses globally. This is likely because the amplification of the negative productivity shocks are greater than that for the

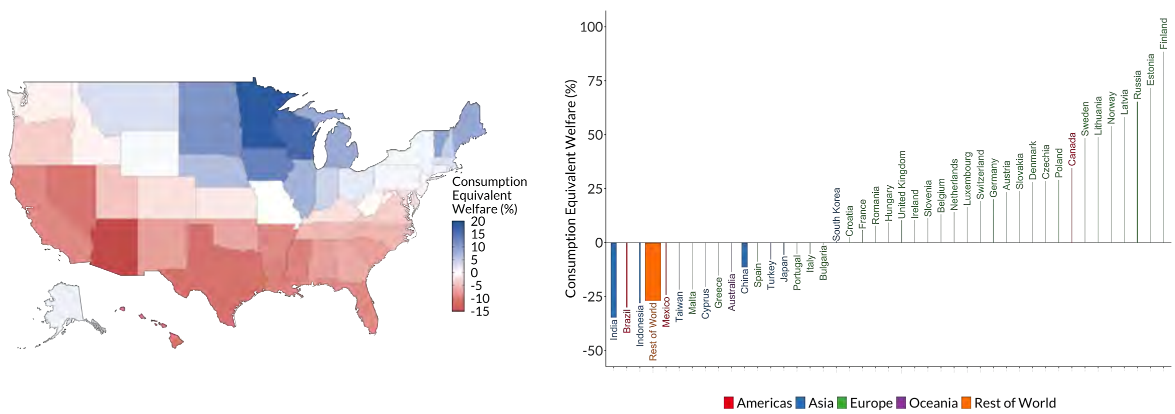
[20]The levels differ because of differences in modeling of climate impacts.

Figure 5: US and global welfare effects in the basic model without market-based adaptation: 2015–2100.

Basic model structure with no market-based adaptation



Full model structure with market-based adaptation



Note: The top row shows the welfare impact of climate change as a constant percent of consumption in our basic model with no amenities, homogeneous response functions, no input-output loops, annual average temperature instead of daily temperature, myopic households, and no changes in trade, migration, or industry switching in response to climate change. The top left panel shows welfare results for each US state. The top right panel shows welfare results for each country where the width of the bar corresponds to the share of the global population. The bottom left and bottom right panels show the same welfare impacts but for our full model with all structural and adaptation channels. All panels use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all panels holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

positive shocks. The amplification of temperature shocks is consistent with the macro-networks literature, which finds that small idiosyncratic shocks can have large aggregate effects as they propagate through supply chains (Acemoglu et al., 2012; Baqaee and Farhi, 2020; Bigio and La'o, 2020; Carvalho et al., 2021).

The third row shows that accounting for direct effects on amenities tends to significantly worsen welfare. The magnitude of the effects on amenities is substantially larger than the effects on productivity. Appendix G.2.2 shows the direct welfare impact of climate impacts on amenities without changes in real wages.

The fourth row shows the effect of replacing our basic model's myopic US households, who only focus on the immediate payoff from their moving decision, with fully forward-looking US households. As expected, dynamics have no impact on welfare if households cannot take advantage of being forward-looking by changing their migration and industry switching decisions. If households are able to adapt, then forward-looking actions increase welfare by 0.2pp in the US, hinting that labor reallocation will have small to moderate aggregate effects. The last two columns show that the global effect of dynamic US households is negligible because the US is a small share of global welfare.

The fifth row shows the effect of replacing the average response function plotted in Figure 2 with the sector-specific temperature response functions in Figure 3. Properly accounting for sectoral heterogeneity generates more negative welfare impacts in the US, but more positive impacts globally.

The sixth row shows the effect of using daily temperature – which better captures exposure to extreme temperatures – instead of using annual average temperature. Properly accounting for daily temperature always worsens welfare. The non-linear, concave temperature response functions imply that annual weather statistics suffer from aggregation bias because of an intuitive Jensen's inequality argument.

The final row shows the effect of adding all attributes to the basic model together, essentially showing the difference between the full model and basic model. Accounting for these novel features generates more negative impacts of climate change. Additionally, notice that in the US, the sum of the welfare effects of adding each attribute individually is about double the size of including all of the attributes together, indicating that there are offsetting non-linear interactions between them.

These results show that proper representation of the properties of the climate-economy matters, and that the interactions have large implications for welfare. The welfare effects of these attributes – even individually – are the same order of magnitude as the total welfare effect, and their inclusion can change the sign of the welfare impacts of climate change. Appendix G.2.1 presents the same results but where we remove each attribute from the full

Table 1: US welfare contribution of model attributes relative to the base model.

	United States		Global	
	Without Market Adaptation	With Market Adaptation	Without Market Adaptation	With Market Adaptation
Basic Structure Welfare	**1.9%**	**2.3%**	**-4.9%**	**-5.5%**
Add Input-Output Linkages	-0.9pp	-0.9pp	+1.2pp	+0.4pp
Add Amenities	-6.2pp	-6.5pp	-18pp	-17.9pp
Add Forward-Looking US Households	+0pp	+0.2pp	+0pp	+0pp
Add Industry Heterogeneity	-0.9pp	-1.1pp	+2.9pp	+3.2pp
Add Daily Temperature	-4.6pp	-5.3pp	-4.3pp	-4.2pp
Add All	-5.9pp	-5.4pp	-16.2pp	-16.2pp

Note:
Rows 2-7 show the difference in welfare between our base model and a model with the listed attribute. All rows use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all rows holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

model instead of adding it to the basic model in order to highlight the non-linear interactions.

3.3 Aggregate Impacts of Climate Change in the Full Model

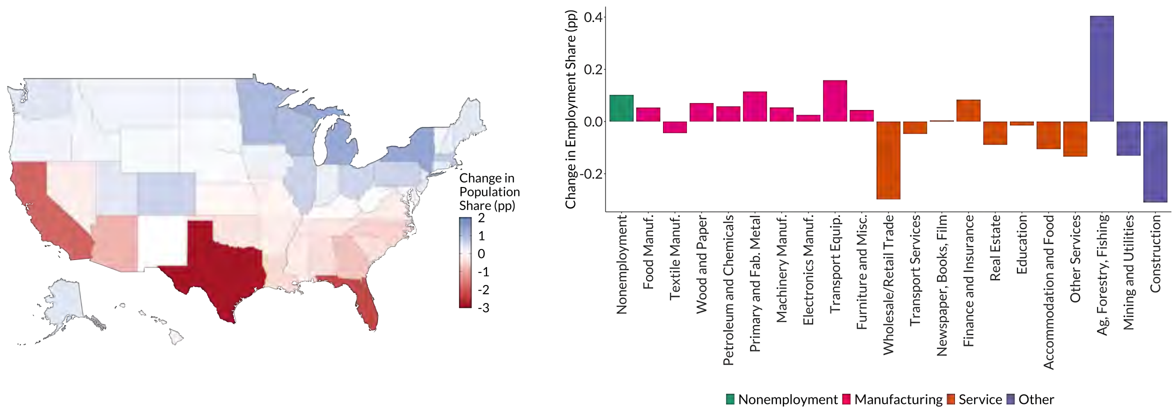
The bottom panels of Figure 5 show the effects of future climate change on welfare in our full model with all structural attributes, and with market-based adaptation. The bottom left panel shows that the relative spatial distribution of welfare impacts is largely the same as in the basic model, but the magnitudes have substantially grown in size. The largest welfare gains are in the upper Midwest with improvements of up to 18% while losses in the Southern part of the US reach 15%. In the aggregate, welfare declines by 3.1%.

The bottom right panel of Figure 5 shows the welfare impacts outside the US. The global average welfare impact, including the US, is a loss of 21.7%. Compared to the top right panel, the dispersion in welfare outcomes across countries is much larger. Countries that had the worst outcomes in the basic model, such as India and Brazil, have significantly larger losses in the full model. Conversely, those countries that had the largest gains in the basic model have even larger gains in the full model. Although Table 1 shows that going from the basic model to the full model has substantial effects on aggregate welfare, it masks how these features exacerbate unequal impacts across rich and poor countries. Omitting these structural economic features will understate the distributional impacts of climate change as well as its regressivity.

3.3.1 Labor Reallocation in the United States

Figure 6 shows how labor reallocates within the US in response to climate change in our full model. The left panel shows the change in population shares for each state. In response

Figure 6: US welfare and population effects with full model structure and market-based adaptation: 2015–2100.



Note: The left panel shows the effect of climate change on state employment shares. The right panel shows the effect of climate change on industry employment shares. Both panels show results from our full model with all structural and adaptation channels. Both panels use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all panels holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

to the heterogeneous impacts across space, households migrate from the South and West to the Midwest, New England, and Alaska. The populations of Michigan, Wisconsin, and Minnesota grow the most, while California, Texas, Florida, and Arizona experience the most out-migration.

The right panel shows the change in employment shares across different industries in the US. The results show an overall decrease in employment by 0.1 percentage points due to decreased wages relative to nonemployment payoffs. In addition, there are substantial increases in the employment shares in agriculture, as well as across most of the manufacturing sector. These gains are offset by declines in services, construction, and mining. Other countries tend to have more severe damages to their agricultural sector, giving the US an increasing comparative advantage and boosting employment in agriculture. Appendix G.2.3 shows the time trends of labor reallocation for each US state and industry, and shows how the trends depend on whether we account for adaptation through trade, forward-looking behavior, or sectoral damage heterogeneity.

3.4 Benefits of Market-Based Adaptation

Now that we have seen how labor adapts in the US, we next quantify the benefits of market-based adaptation to understand its role in the level and spatial distribution of US welfare gains. We consider two endogenous responses to changes in climate: changing trade shares, and changing labor reallocation shares.

Table 2 reports welfare effects for the two adaptation mechanisms. We compute the welfare impact of adaptation by simulating the full model with all possible combinations of the adaptation channels, and then comparing against the welfare results of the full model without adaptation which generates a welfare loss of 4.1% in the US. Formally, let δ_f be the population-weighted average of all δ_n^k's in the US in our full structural model with all the attributes in Table 1 added. Let δ_f^{+A} denote the welfare effect of climate change from a model with adaptation mechanism A added. Our measure of the welfare effect of adaptation reported in Table 2 is:

$$\Delta_f^A := \delta_f^{+A} - \delta_f.$$

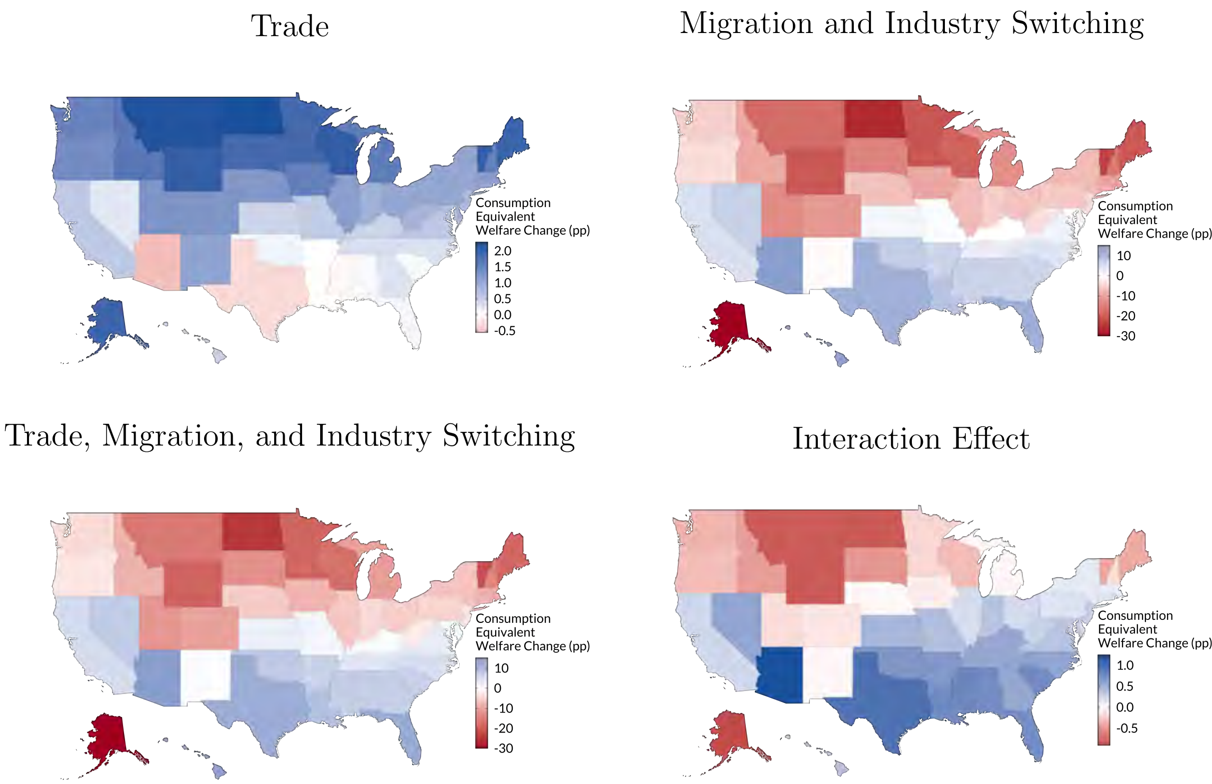
Column 1 reports the impact of climate change on US welfare in the full model without market-based adaptation: -4.1%. Columns 2–4 show the difference in US welfare in models where we turn on different combinations of adaptation mechanisms relative to the first column. The second column shows that adaptation through changing trade shares alone improves US welfare by 0.688 pp,[21] while the third column shows that adaptation through the labor market alone has little aggregate effect. The last column shows that trade and labor reallocation interact and are complementary: including both together yields larger welfare gains than the sum of their individual welfare gains. The headline number is that the adaptation channels combined improve welfare by 1pp, offsetting the negative impacts of climate change by a quarter. This aggregate complementarity arises because forward-looking labor reallocation lets households better take advantage of adjustments through trade by moving to the places that benefit the most from trade.

Figure 7 shows the spatial distribution of the welfare effects of adaptation reported in Table 2 and provides insight into the aggregate complementary between trade and labor adaptation. The first three panels correspond to Columns 2, 3, and 4 of Table 2, and the last (bottom right) panel plots the total interaction or complementarity effect: the difference between Column 4 and the sum of Columns 2 and 3. The population-weighted average value across all states in the figure corresponds to the values reported in the table. Each map has a different scale to better display the spatial distribution of welfare.

The top left map shows the welfare value of trade adjustments. Trade makes Northern US states better off by moderate margins, with the largest gains in the Northeast and Upper Plains. Trade allows Northern states, which are generally slightly better off under climate change even without trade, to adjust consumption patterns and purchase products

[21] Globally, trade adaptation improves welfare by 0.8pp.

Figure 7: Welfare value of adaptation mechanisms: 2015–2100.



Note: Each state is colored according to its state-specific Δ_f^{+A} computed from comparing our full model relative to a model with one or more of the shares fixed. The top left panel holds trade shares fixed at their no climate change trajectories. The top right panel holds migration shares and industry switching shares fixed at their no climate change trajectories. The bottom left right panel holds all three fixed at their no climate change trajectories. The bottom right is the difference between the bottom left panel and the sum of the top two panels. The welfare numbers for each state are computed identically to columns 2, 3, and 4 in Table 2 and the population-weighted average across all states matches the values in the table. All panels use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all panels holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

Table 2: US welfare contribution of adaptation through trade, migration, and industry switching: 2015–2100.

Full Structure Welfare	Add Trade Adjustments	Add Migration and Industry Switching	Add All
-4.064%	+0.668pp	+0.004pp	+1.004pp

Note:
Each row shows the difference in welfare between our full model without market-based adaptation, and a model with the listed adaptation mechanism. All rows use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all rows holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

from lower-cost sources, raising real wages. Similarly, trade allows other locations to adjust consumption patterns and purchase products produced in the relatively more productive North, raising their real wages and welfare even further.

Some states in the South are actually made worse off when trade can adjust, but labor cannot reallocate in response to climate change. When trade patterns can adjust, the additional extreme heat in the South substantially decreases the probability that their sellers are lowest-cost – effectively increasing trade competition for these producers – and induces buyers to procure goods from other locations instead. This adjustment margin reduces labor industry income in locations with hard-hit industries which reduces welfare even beyond the direct reduction in productivity. This effect is larger than the benefits the South obtains from being able to adjust consumption patterns through trade in order to buy lower cost goods. In Appendix G.2.4 we decompose this into a pure trade competition effect and an input-output amplification effect.

The top right map shows the welfare value of migration. The benefits of migration follow the opposite pattern of trade. Alaska and Northern states are made worse off because households from other states migrate north and depress real wages for incumbent households. Southern households are better off because they can migrate to the Midwest, Northeast, or Alaska which have higher productivity and better amenities under climate change relative to their origin state. Although some states are worse off with migration because of these pecuniary externalities, the average welfare effect is a marginal gain.

The bottom left map shows the state-specific effects of trade and labor reallocation combined which are dominated by the welfare effects of labor reallocation. Alaska is significantly worse off because of market-based adaptation; because of its small population, the negative effects of in-migration on incumbent households' real wages dominates any welfare gains from industry switching and trade adjustments. States in the South value adaptation the most and have welfare improvements of up to 10pp due to all adaptation mechanisms. Southern households migrate North and switch into more productivity industries, allowing them to overcome the local negative trade impacts. Complementarities between trade and labor reallocation improve welfare by 50 percent more than the sum of the individual trade, migration, and industry switching effects. Adaptation to climate change has strong progressive impacts on the US: the correlation between the benefits from adaptation and state income in 2015 is -0.40.[22]

The bottom right panel pulls out the aggregate complementarity or interaction effect between the adaptation mechanisms: the welfare impact of full adaptation in the bottom left map minus the sum of the individual adaptation benefits in the top two maps. If there were no interactions between the adaptation margins then this map would show zeros everywhere. The interaction of the different mechanisms generally amplifies the overall effect of adaptation. The South gains because of how trade interacts with labor market reallocation. Without labor market reallocation, trade makes the South worse off, but with labor market reallocation, the effect of trade flips. Southern households can now migrate North and take advantage of the additional benefits the North reaps from trade. The interactions have the opposite effect and exacerbate pecuniary externalities on incumbent households in the North because trade increases the amount of migration, depressing real wages even further than compared to a world without trade adjustments. The interaction effect comprises a non-negligable share of the welfare impacts shown in Figure 5.

4 Estimating the Welfare Impacts of Climate Change: A Reduced Form Approach

Our quantitative results consist of three main findings. First, climate change impacts through productivity and amenities will severely reduce global welfare, but with substantial differences across countries and US states.[23] The negative effects will be borne by lower-income regions, while richer regions tend to gain. Second, the US will suffer welfare losses from

[22]Damages tend to be regressive: the correlation between the negative impacts of climate change and state income in 2015 is -0.32.

[23]Recall that in non-US countries we assume that workers can switch across industries without any cost, there is no cross-country migration, but in the US there is within-country migration and industry switching with positive – but not infinite – frictions.

climate change, largely driven by climate impacts on amenities and extreme temperature. Third, market-based adaptation has a substantial influence on welfare. In the US, adaptation reduces welfare losses from climate change by a quarter, and has significant benefits to lower-income states in the South.

To quantify reallocation and decompose the value of different model attributes and adaptation mechanisms we needed to impose significant structure on the economy. *A priori* it is unclear whether these assumptions – such as temperature affecting the level of productivity and local amenities, or households being perfectly forward-looking – are a good fit to reality. We validate our quantitative model assumptions – many of which are commonly used in quantitative models of climate change – by introducing a new reduced form approach for estimating the welfare impacts of climate change while accounting for dynamic and spatial behavior. We start our reduced form approach by introducing a formal dynamic spatial model of household location and industry choice similar to the one in our quantitative model but with significantly less structure. We then show how the dynamic discrete choice problem for a single household can be recast as a dynamic continuous choice problem for a representative household in each region. The continuity of choices allows us to apply the envelope theorem, thereby extending the existing literature employing a static approach (e.g. Deschênes and Greenstone, 2007; Guo and Costello, 2013; Hsiang, 2016; Deryugina and Hsiang, 2017). The primary challenge for a dynamic envelope theorem approach is recovering the household's expected value as a function of observables.[24] One of the innovations in our paper is showing how to do so while imposing relatively few assumptions on the overall economy.

4.1 A General Dynamic Model of Household Location and Industry Choice

Our starting point for the reduced form approach is the household model in Section 1, but where we relax assumptions on the functional form of flow utility. Households in each market (n, k) receive flow utility given by a general function $U^k_{n,t}$ at time t which may be a function of consumption, local weather, climate adaptation efforts, and other inputs. The optimization problem for a household in market (n, k) at time t is:

$$v^k_{n,t} = \max_{\{i,s\}_{i=1,s=0}^{N,K}} U^k_{n,t} + \left\{\beta \mathbb{E}_\epsilon \left[v^s_{i,t+1}\right] - \mu^{ks}_{ni} + \nu \epsilon^s_{i,t}\right\}$$

[24]This complements Lemoine (2021) which shows how to correctly compute welfare impacts of climate change in a dynamic setting. We build upon this work by relaxing the assumption of a steady state and by leveraging a dynamic discrete choice structure which does not require any information on forecasts.

Recall that $V_{n,t}^{k} \equiv \mathbb{E}_{\epsilon}\left[v_{n,t}^{k}\right]$, and that the Type-I Extreme Value assumption on the idiosyncratic shocks delivers the following migration share expression:

$$\pi_{ni,t}^{ks} = \frac{\exp\left[\left(\beta V_{i,t+1}^{s} - \mu_{ni}^{ks}\right)/\nu\right]}{\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta V_{l,t+1}^{h} - \mu_{nl}^{kh}\right)/\nu\right]}. \tag{22}$$

4.2 Existence of a Representative Household

One challenge in our setting is that individual households in our model are optimizing by making a discrete choice of actions – specifically, which market to migrate into next period – rather than a continuous one. The discreteness of the problem allows for a marginal change in climate to induce a change in actions if a household is sufficiently close to a threshold welfare value (Guo and Costello, 2013). In this case the envelope theorem may not apply and weather variation may not identify the effect of a change in climate. We circumvent this issue by taking advantage of the fact that there is a mass of households in each location and that there exists a representative household for discrete choice problem with a Type-I Extreme Value idiosyncratic shock (Anderson et al., 1988). The representative household in each market (n, k) aggregates the individual discrete decisions and makes *continuous* choices of a set of migration probabilities from (n, k) to all markets (i, s): $\pi_{ni,t}^{ks} \in [0, 1]$. Formally,

Proposition 1. *A representative household problem consistent with the individual household's discrete choice problem with aggregate migration shares* (22) *is given by:*[25]

$$V_{n,t}^{k} = \max_{\{\pi_{ni,t}^{ks}\}_{i=1,s=0}^{N,K}} U_{n,t}^{k} + \sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks}\left[\beta\left(V_{i,t+1}^{s}\right) - \mu_{ni}^{ks}\right] - \nu\sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks}\log\pi_{ni,t}^{ks} \tag{23}$$
$$s.t \quad \sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks} = 1, \qquad 0 < \pi_{ni,t}^{ks} \leq 1 \quad \forall\, n, i, k, s, t.$$

[25] To see this, note that the first-order conditions for (23) are

$$\left[\beta\left(V_{i,t+1}^{s}\right) - \mu_{ni}^{ks}\right] - \nu\left[\pi_{ni,t}^{ks}\frac{1}{\pi_{ni,t}^{ks}} + \log\pi_{ni,t}^{ks}\right] - \rho = 0,$$

$$1 - \sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks} = 0,$$

where ρ is the Lagrange multiplier for the constraint. The first equation implies $\pi_{ni,t}^{ks} = e^{\left[\beta\left(V_{i,t+1}^{s}\right)-\mu_{ni}^{ks}\right]/v}e^{-1-\rho/\nu}$. Substituting into the constraint $\sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks} = 1$ implies $e^{1+\rho/\nu} = \sum_{i=1}^{N}\sum_{s=0}^{K}e^{\left[\beta\left(V_{i,t+1}^{s}\right)-\mu_{ni}^{ks}\right]/v}$. Substituting this into the expression for $\pi_{ni,t}^{ks}$ above yields the result.

The first summation term in the objective captures the continuous analogue of the individual household problem if the idiosyncratic shocks were omitted: a migration share weighted average of continuation values net of moving costs. The second summation term is a quasi-love-of-variety effect for the representative household. The T1EV idiosyncratic shocks generate dispersion in payoffs across otherwise identical individual households in (n, k), which then generates dispersion in the location choices of the individual households and evens out the migration share choices by the representative household. Notice that if ν is large, then the shock $\epsilon_{i,t}^{s}$ tends to dominate location-specific payoffs relative to the expectation of future utility flows $\left(V_{i,t+1}^{s}\right)$ for an individual household. In the limit as $\nu \to \infty$, then the payoff is entirely determined by the idiosyncratic shock and individual households have equal probability of moving to any market since the shocks are iid. For the representative household, $\nu \to \infty$ implies $\pi_{ni,t}^{ks} \to \frac{1}{NK} \quad \forall n, i, k, s, t$ and all the choice probabilities are equal. If ν is small then future utility flows dominate the representative household's payoff. In the limit as $\nu \to 0$, there is less and less difference in the potential payoffs of the individual households in (n, k), and so they will all increasingly migrate to the same market (i, s) where $\left(V_{i,t+1}^{s}\right) - \mu_{ni}^{ks}$ is the highest. This is equivalent to the representative household in (n, k) putting a probability of one on the location with the highest value in the limit as $\nu \to 0$.

4.3 Climate, Weather, and the Dynamic Spatial Envelope Theorem

We now introduce the climate structure formally, building on the prior climate impacts literature (e.g. Hsiang, 2016; Lemoine, 2021). Define $\mathbf{C_{n,t}}$ as the local climate in region n at time t, which is a function of location-specific variables such as elevation, latitude, and longitude, and time-specific variables such as atmospheric CO_2 concentrations. Define $\mathbf{T_{n,t}}$ as the vector of observed weather variables in region n at time t. These are a function of the local climate and given by: $\mathbf{T_{n,t}} = \mathbf{C_{n,t}} + \varepsilon_{\mathbf{n,t}}^{\mathbf{C}}$, the climate plus an additively separable, mean zero, iid noise term $\varepsilon_{\mathbf{n,t}}^{\mathbf{C}}$. The observed weather $\mathbf{T_{n,t}}$ will not necessarily equal the climate $\mathbf{C_{n,t}}$, which is just the long-run expected weather and our object of interest.

Now that we have defined the mapping from climate to weather, we can apply the envelope theorem to the representative household's dynamic spatial decision problem to show that weather variation identifies climate variation. Let ρ be the Lagrange multiplier associated with the representative household's constraint on the sum of migration shares. Denote $\mathcal{L}_{n,t}^{k}$

as the Lagrangian associated with (23):

$$\mathcal{L}_{n,t}^{k}(\cdot) := U_{n,t}^{k} + \sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks}\left[\beta V_{i,t+1}^{s} - \mu_{ni}^{ks}\right] - \nu\sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks}\log\pi_{ni,t}^{ks} + \rho\left[1 - \sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks}\right]. \tag{24}$$

Differentiating equation (24) with respect to the one-period-ahead local climate and applying the constrained optimization envelope theorem gives us the following:[26]

$$\frac{\partial V_{n,t}^{k}}{\partial \mathbf{C_{n,t+1}}} = \underbrace{\sum_{i=1}^{N}\sum_{s=0}^{K}\underbrace{\frac{\partial \mathcal{L}_{n,t}^{k}}{\partial \pi_{ni,t}^{ks}}}_{=0}\frac{\partial \pi_{ni,t}^{ks}}{\partial \mathbf{C_{n,t+1}}}}_{\text{indirect effect } = 0} + \underbrace{\sum_{i=1}^{N}\sum_{s=0}^{K}\frac{\partial \mathcal{L}_{n,t}^{k}}{\partial V_{i,t+1}^{s}}\frac{\beta\partial V_{i,t+1}^{s}}{\partial \mathbf{T_{n,t+1}}}\underbrace{\frac{\partial \mathbf{T_{i,t+1}}}{\partial \mathbf{C_{i,t+1}}}}_{=1}}_{\text{direct effect}}$$

where $\frac{\partial \mathcal{L}_{n,t}^{k}}{\partial \pi_{ni,t}^{ks}} = 0$ from the representative household's first-order condition, and $\frac{\partial \mathbf{T_{i,t}}}{\partial \mathbf{C_{i,t}}} = 1$ by definition. The following proposition summarizes the result.

Proposition 2. *The effect of a change in some climate variable is just the direct effect of the observed weather variable on future value, that is,*[27]

$$\frac{\partial v_{n,t}^{k}}{\partial \mathbf{C_{n,t}}} = \sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks}\beta\frac{\partial \mathbb{E}_t\left(V_{i,t+1}^{s}\right)}{\partial \mathbf{T_{n,t}}}.$$

Intuitively, at an optimum, the indirect effect of changes in household actions in response to a change in climate do not have first-order welfare effects (Guo and Costello, 2013; Hsiang, 2016; Deryugina and Hsiang, 2017). The only relevant effect is the direct impact of temperature on payoffs: a migration share weighted average of *temperature* impacts on continuation values. In other words, the only pathway for a change in climate to affect welfare is through its direct effects on payoffs which happens through realizations of temperature. Thus, as noted in the previous literature, if an outcome is being maximized, then the effect of a change in weather identifies the effect of a change in climate. Our contribution is showing how to implement this insight in a dynamic spatial framework.

[26] We differentiate using one period ahead variables to avoid impacts on current flow payoffs which are not identified with our approach.

[27] Notice that if we were estimating the impact of climate change on a variable that is not maximized, for example wages, then the first term may not be zero. We would need additional data on wages and a way to pin down how actions affect wages because of changes in climate.

4.4 In-Migration Identifies Climate Effects

To apply the dynamic spatial envelope theorem from the previous section we need: (1) to recover the household expected value function from observables, and (2) have the household expected value function capture the welfare of the local economy. To satisfy the second condition we make one assumption:

Assumption 1. *Firms make zero profit, or households in each market* (n, k) *own firms in* (n, k) *at time* t*.*

Note now that the denominator in equation (22) is identical across all destination markets at time t within an origin market. We relabel it $\exp(\tilde{\delta}_{n,t}^k) \equiv \sum_{l=1}^N \sum_{h=0}^K \exp\left[\left(\beta V_{l,t+1}^h - \mu_{nl}^{kh}\right)/\nu\right]$. Next, notice that the numerator is multiplicatively separable into the expected continuation value and the bilateral moving cost. Solving for the expected value term in the numerator then gives us the following expression:

$$V_{i,t+1}^s = \frac{\nu}{\beta}\log \pi_{ni,t}^{ks} + \frac{1}{\beta}\mu_{ni}^{ks} + \frac{\nu}{\beta}\tilde{\delta}_{n,t}^k.$$

We can express a market's expected value as the sum of log in-migration flows, a bilateral time-invariant component, and component specific to each origin-year. This is similar in spirit to Hotz and Miller (1993) which provides an approach to recover expected values as a function of choice probabilities – which are the same as our migration shares – and parameters to be estimated. Here we show how expected values are a function of migration shares and a set of fixed effects allowing us to estimate marginal effects of a change in climate.

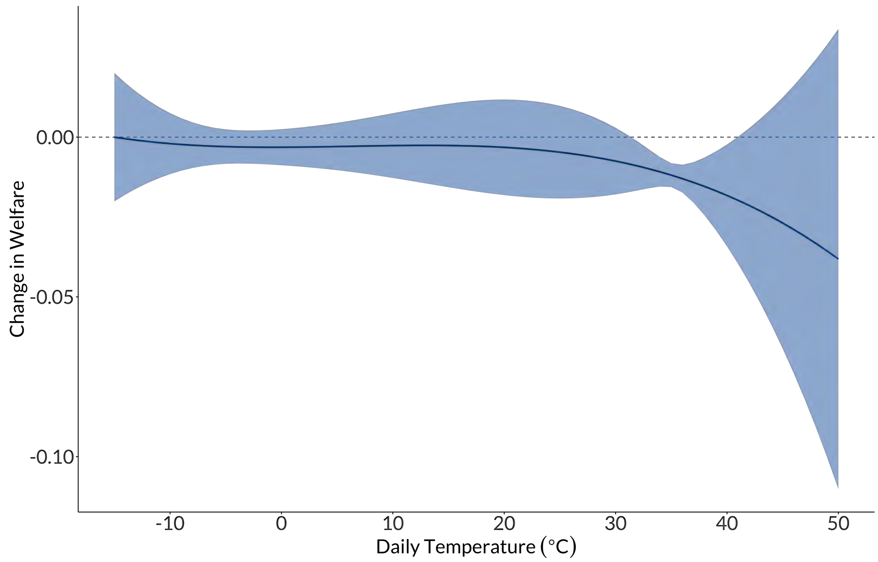
Now that we have a closed form expression for the expected value at time $t+1$, we can write down the following regression of migration shares on temperature variables and fixed effects:

$$\log \pi_{ni,t}^{ks} = \frac{\beta}{\nu} h(\mathbf{T_{i,t+1}}; \zeta_{\mathbf{D}}) + \delta_{n,t}^k + \varphi_{ni}^{ks} + \varepsilon_{ni,t}^{ks} \tag{25}$$

where $h(\mathbf{T_{i,t+1}}; \zeta_{\mathbf{D}})$ is our *climate* response function which depends on a vector of temperature variables $\mathbf{T_{i,t+1}}$ and a set of parameters to be estimated $\zeta_{\mathbf{D}}$. h tells us the welfare impacts of a long-run change in the local temperature distribution. The fixed effects are to control for the destination's migration costs and the common time component.

Before continuing it is instructive to note what assumptions we have *not* made in the model in order to clarify what this approach captures. First, no where in the model have we assumed how weather affects the economy. This leaves open the possibility that weather can affect the level of output, the level of utility, the growth rate of productivity, accumulation of human capital, human mortality, and other economic variables. Second, we have

Figure 8: The dynamic envelope theorem welfare-climate response function.



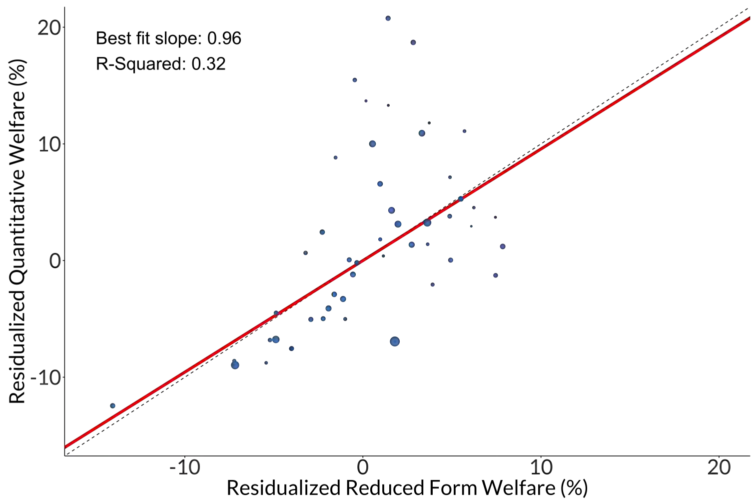
The response function is constructed using a third-degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are winsorized at -15°C and 50°C. The shaded area denotes the 95% confidence intervals. The response function is estimated using equation (25). Standard errors are clustered two ways at the origin state and destination state. The peak of the response function has been normalized to zero for plotting.

made no assumptions on the functional forms for utility or production besides the additive idiosyncratic shocks and additive moving costs. Third, we have made no assumptions on how households and firms adapt to climate change except that households make a discrete location and industry choice. These features allow us to stay agnostic about the structure of production and utility, and precisely how climate change and adaptation affect the economy, while still recovering the effects of a change in climate. The main limitation of this approach is that we only have bilateral migration shares within the US and thus can only compute US welfare. In principle it could be applied globally with the necessary bilateral migration data.

4.5 Dynamic Envelope Theorem Results

Figure 8 plots the reduced form climate response function estimated from equation (25). The response function is inverse-U shaped and peaks at a daily temperature of 10°C. The estimates indicate that if a region has a single hot day at 35°C instead of at the optimal temperature of 10°C welfare in that year declines by 2.0%. An extreme cold day at -15°C only reduces welfare by 0.7%. Appendix G.2 shows that this response function is robust to

Figure 9: Reduced form welfare versus structural welfare.



Scatterplot of the quantitative model's welfare predictions for each US state versus the reduced form model's welfare predictions. The dashed line is the 45 degree line. The red line is the best fit line. The quantitative model is our full model with all structural and adaptation channels. Both models use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

alternative estimation approaches.

4.6 Model Validation

We shock US states with the same projected changes in climate used in the quantitative simulations to generate predicted reduced form welfare impacts that serve as an apples-to-apples comparison to our quantitative results in Section 3.

Figure 9 plots the quantitative results against the reduced form results. Each state is scaled by the size of its population, the dashed line is the 45 degree line and the red line is the best fit line. Three points stand out. First, the points fall close to the 45 degree line and the best fit slope is nearly 1.[28] This means that, on average, cross-region differences in welfare in the reduced form model quantitatively match that of the quantitative model. Second, the R-squared is moderately high indicating that the predictions of the two models for individual regions are closely correlated. The fit between the two approaches is better for regions predicted to have worse welfare losses. These two facts gives us confidence that the distribution of our findings across locations is accurate. Last, on average, the

[28]The results are essentially identical if we weight states by their population, or if in the quantitative model we shock US states one-by-one with the RCP 4.5 scenario across 50 different simulations instead of using the single full global shock simulation.

quantitative welfare estimates are about 12pp higher than the reduced form estimate. The slope being approximately 1, the strong correlation, and the upward bias combined suggests there is a missing piece in the quantitative model that should capture some force that reduces welfare almost everywhere by approximately the same amount, such as the perfect foresight assumption or missing a common negative impact of climate change. In total, this gives us confidence in our qualitative and distributional findings, and signals that the levels of our quantitative findings should be shaded down.

5 Conclusion

In this paper we develop two approaches evaluating the economic impacts of climate change in dynamic spatial equilibrium. In our first approach we develop a dynamic spatial quantitative model where temperature affects industrial productivity and local amenities. Our modeling approach allows us to tightly link our model to the data and simulate counterfactual outcomes without requiring information on the levels of non-temperature fundamentals such as migration costs, trade costs, or productivity. Our model and results have several implications for the effects of climate change, and the extent to which market forces can aid the economy in adapting to these changes.

First, our main quantitative result is that market adaptation is economically significant and offsets one quarter of the welfare losses in the United States. Adaptation is most important for Southern states that are exposed to the greatest negative effects of climate change, with some states valuing the ability to adapt through market mechanisms at over 10% of their consumption levels. This only holds true when both trade and labor can reallocate, trade adjustments alone actually make the South worse off and are regressive.

Second, we provide two new ways to estimate the effects of temperature on firm productivity and on household utility. Our model shows that in spatial equilibrium, productivity effects are well-identified using common trade data, making this an attractive way to estimate impacts while accounting for spatial spillovers often overlooked in prior research. In Section D.3 in the appendix we show that spatial considerations also matter because the economy and climate are linked across space, which results in violations of standard identifying assumptions. Similarly, our model shows that we can estimate the effect of temperature on household utility, even when households are dynamically optimizing, given we have data on migration flows and wages to control for forward-looking behavior and effects on productivity and consumption of goods. Appendix Section D.3 shows that accounting for dynamics in estimation has first-order effects.

In our second approach we show how observable migration data allow us to estimate the welfare impacts of climate change under relatively few assumptions. This approach provides a path forward for empirical researchers to advance the burgeoning literature aiming to estimate effects of climate change from weather data in reduced form settings, and it also provides a roadmap for researchers working on quantitative aspects of climate change and labor reallocation to validate their models. Our dual approaches complement one another by having differing levels of assumptions and ability to quantify different climate impacts. Both approaches are able to quantify welfare and thus we can compare results to gain further insights about how to structure quantitative models.

Overall, this paper shows the importance of heterogeneity, model structure, and market adaptation for quantifying the impacts of climate change. Important steps not taken in this paper may affect welfare and should be explored in future work. Our quantitative model focuses on labor-side mechanisms and ignores that firms behave dynamically and also invest in climate adaptation. Better accounting for firm-side adaptive responses would further increase any benefits and decrease any losses from climate change. We also abstract away from impacts on capital, and impacts of climate change that are not directly through temperature, such as sea level rise inundating coastal regions (Balboni, 2019; Desmet et al., 2021; Fried, 2021), or cyclone strikes (Bakkensen and Barrage, 2021). This will understate the costs of climate change as well as the benefits of migration and trade as adaptation mechanisms.

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Appendices

A Industry List

Here we list the set of 20 industries by NAICS codes and give examples for what would fall into each.

Agriculture

NAICS 11: Agriculture, Forestry, Fishing, and Hunting

Manufacturing

NAICS 21-22: Mining and Utilities
NAICS 23: Construction
NAICS 311-312: Food Manufacturing
NAICS 313-316: Textiles, Apparel, Leather Manufacturing
NAICS 321-323: Wood, Paper, and Printing
NAICS 324-327: Petroleum, Chemicals, Plastics, Minerals Manufacturing
NAICS 331-332: Primary Metal and Fabricated Metal Manufacturing
NAICS 333: Machinery Manufacturing
NAICS 334-335: Computers, Electronics, and Appliances Manufacturing
NAICS 336: Transportation Equipment Manufacturing
NAICS 337-339: Furniture and Miscellaneous Manufacturing

Services

NAICS 42-45: Wholesale Trade and Retail Trade
NAICS 481-488: Transport Services
NAICS 511-512: Newspaper, Books, Software, Motion Pictures, and Music Production
NAICS 521-525: Finance and Insurance
NAICS 531-533: Real Estate
NAICS 61: Education
NAICS 721-722: Accommodation and Food Services
NAICS 493, 53, 541, 55, 562, 81: Other Services

B Details on Climate Module

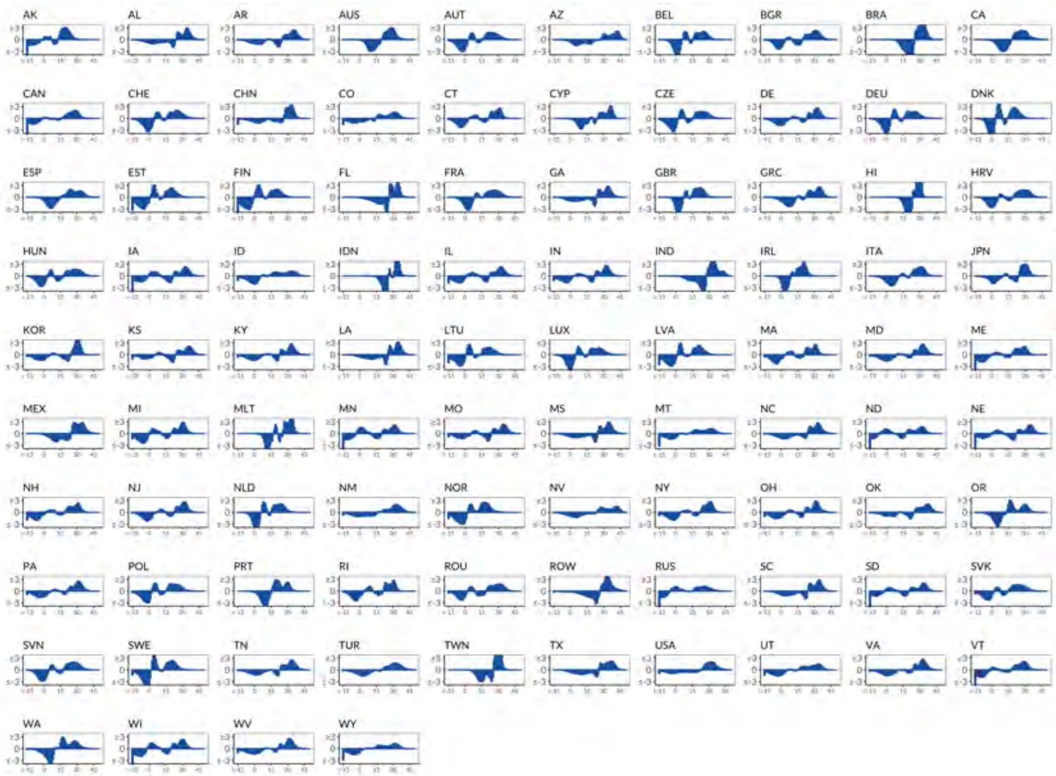
B.1 Global Climate Module List

Here we list the set of 17 CMIP5 Global Climate Modules (GCMs) used in our simulations.

ACCESS1-0
BNU-ESM
CanESM2
CCSM4
CESM1-BGC
CNRM-CM5
CSIRO-Mk3-6-0
GFDL-CM3
GFDL-ESM2G
GFDL-ESM2M
IPSL-CM5A-LR
IPSL-CM5A-MR
MIROC-ESM-CHEM
MPI-ESM-LR
MPI-ESM-MR
MRI-CGCM3
NorESM1-M

B.2 Global Change in Temperature Distribution Under RCP 4.5

Figure B.1: Change in within-year daily temperature distributions: 2015–2100.

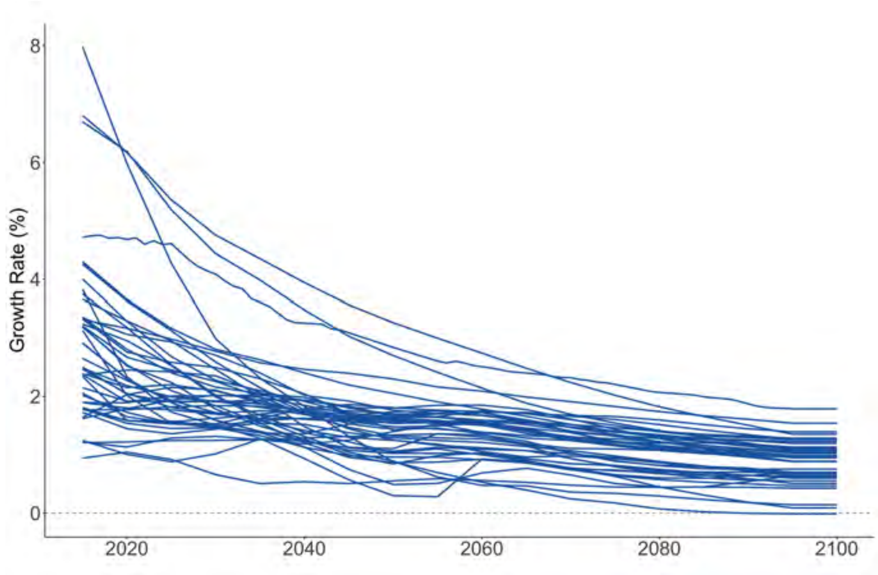


Note: Each plot shows the state-specific change in the number of days in each 1°C temperature bin from the first to last year of the RCP 4.5 climate scenario, averaged over 17 GCMs. Positive numbers denote increases in days at that temperature, negative numbers denote decreases. The temperature distributions are winsorized at -15°C and 50°C.

B.3 Growth Rate Trajectories under Shared Socioeconomic Pathway SSP2

Figure B.2 plots the growth rate trajectories for each region in our model. There is significant variation across space, but all regions are expected to grow at slower rates over time.

Figure B.2: SSP2 country-specific growth rates.



Note: The values are linearly interpolated between every 5 years.

C Data for Estimation and Simulations

C.1 Data for Estimation of Response Functions

We use data on bilateral trade expenditures from the World Input Output Database (WIOD) (Timmer et al., 2015). The WIOD reports bilateral trade flows for 43 countries and an aggregate for the rest of the world from 2000–2014. Data are reported for 56 different industries, but we aggregate these up to 20 industries to match the other data required for the counterfactual simulations similar to CDP.

We integrate our economic data with temperature and precipitation data from Princeton's Global Meteorological Forcing Dataset (GMFD) for land surface modeling.[29] The GMFD provides gridded daily data on temperature and precipitation over 1948-2016 with a 0.25 degree spatial resolution (around 28 km at the equator). We spatially aggregate the gridded data to each country based on population weights from 2010 (Center for International Earth Science Information Network, 2018).

Data on time-varying non-tariff trade costs come from the CEPII Gravity Dataset. Data on tariff rates come from the World Integrated Trade Solution (WITS) database. WITS reports tariffs at the 4 digit NAICS level which we aggregate up to our 20 industries using a weighted average with the weights given by the import share of each 4 digit NAICS code.

C.2 Data for Simulations

Data for the initial period of the simulations come from the following sources: the World Input Output Database (WIOD), the Bureau of Economic Analysis (BEA), The Organization for Economic Cooperation and Development (OECD), the 2012 and 2017 U.S. Commodity Flow Surveys (CFS), the 2015 American Community Survey (ACS), and the U.S. 2015 Current Population Survey (CPS). Here we describe how we calibrate model parameters and construct time series of variables along with the data sources for each. Much of the calibration follows from CDP.

C.2.1 Labor Share of Value Added

Non-US Countries The WIOD reports value added for each industry-country-year. We combine this with data from the OECD on labor compensation as a fraction of value added. The OECD data are not reported for all countries so we impute for the missing values with the median of the observed countries.

States We use data from the BEA to compute value added as GDP net of taxes and subsidies, as well as total labor compensation for each industry-state. The labor share of value added is the ratio of these two values.

[29] `https://hydrology.princeton.edu/data.pgf.php`

C.2.2 Bilateral Trade Flows

Across Countries Bilateral trade flows across countries comes from the WIOD.

Across US States Bilateral trade flows across states comes from a linear interpolation between the 2012 and 2017 CFS. We use these cross-state bilateral trade flows to construct expenditure shares for each industry. For industries not in the CFS, we impute expenditure shares as the state-level expenditure share across all observed industries. We then multiply each state's industry expenditure share by the US total industry domestic expenditures in the WIOD to recover cross-state bilateral trade flows that match the level of total US domestic expenditures in the WIOD data.

Between US States and Other Countries First, we use the BEA data on industry employment to construct state employment shares for each industry. We then assign each state's bilateral expenditures with non-US countries to be the product of the employment share in the industry and the US total bilateral expenditures in the industry.

C.2.3 Value Added Share of Gross Output

We construct gross output for each country and state using the previously constructed bilateral expenditures. We obtain value added as described above. The share of value added in gross output in the ratio of these two values. For industries not in the CFS, we do not have gross output so we impute their value added share to be the median of the observed industries.

C.2.4 Intermediates Share of Gross Output

We construct the share of each industry using expenditures on intermediates in the WIOD. We then scale these values using the value added share of gross output so that the sum of the value added share and all intermediates shares is equal to 1.

C.2.5 Consumption Shares

We construct consumption shares, common across all states and countries, using the WIOD as the ratio of industry spending to total spending.

C.2.6 Local Capitalist Share of the Global Portfolio

We construct local capitalist shares identically to CDP. We use year 2015 WIOD data to construct the trade imbalance at each location, TI_n. We combine this with our estimates of value added and the share of local structures in value added to get the local capitalist shares:

$$\iota_n = \frac{\sum_{k=1}^{K} \psi^k VA_n^k - TI_n}{\sum_{n=1}^{N} \sum_{k=1}^{K} \psi^k VA_n^k}.$$

C.2.7 Labor and Structure Value Added

We get value added for labor and structures using the structure share of value added in conjunction with the value added estimates described above.

C.2.8 Migration Shares

We use annual data on migration across states from the Public Use Micro Sample (PUMS) of the 2015 ACS, and monthly data on migration across sectors using the 2015 CPS to construct an annual transition matrix across markets following the method in CDP.

C.2.9 Initial Distribution of Labor

We use the 2015 ACS to compute the initial distribution of labor. We include individuals between 25 and 65.

D Derivation of Estimating Equations and Comparison to Alternative Approaches

In this appendix we derive estimating equations for the effect of a change in the distribution of daily temperature on productivity and amenities. We then show how analogous estimating equations derived from models that ignore spatial linkages or forward-looking behavior result in biased estimates.

D.1 Derivation of Estimating Equation for Effects on Productivity

From equations (12) and (13) we can write the expenditures of region n on industry k goods from region i as:

$$X_{ni,t}^{k} = \left(\Gamma^{k}\right)^{-\theta^{k}} \frac{Z_{i,t}^{k}\left(x_{i,t}^{k}\right)^{-\theta^{k}}\left(\tau_{ni,t}^{k}\right)^{-\theta^{k}}}{\left(P_{n,t}^{k}\right)^{-\theta^{k}}} X_{n,t}^{k}.$$

Normalizing the above equation by the importer's own expenditures X_{nn}^{k} in industry k gives:

$$\frac{X_{ni,t}^{k}}{X_{nn,t}^{k}} = \frac{Z_{i,t}^{k}\left(x_{i,t}^{k}\right)^{-\theta^{k}}\left(\tau_{ni,t}^{k}\right)^{-\theta^{k}}}{Z_{n,t}^{k}\left(x_{n,t}^{k}\right)^{-\theta^{k}}}.$$

Using equation (11) to substitute in for the Z^{k} terms, taking the logarithm on both sides, and rearranging we obtain:

$$\begin{aligned}\log\left(\frac{X_{ni,t}^{k}}{X_{nn,t}^{k}}\right) = {} & \left[g(\mathbf{T}_{i,t};\zeta_{\mathbf{Z}}^{k}) - g(\mathbf{T}_{n,t};\zeta_{\mathbf{Z}}^{k})\right] + \log\left(\frac{\bar{Z}_{i,t}^{k}}{\bar{Z}_{n,t}^{k}}\right) \\ & - \theta^{k}\log\left(\tau_{ni,t}^{k}\right) - \theta^{k}\log\left(\frac{x_{i,t}^{k}}{x_{n,t}^{k}}\right)\end{aligned}$$

which matches equation (17) in the paper.

D.2 Derivation of Estimating Equation for Effects on Amenities

We now show how to derive the estimating equation for effects of temperature on utility. To estimate the effect of temperature on amenities, we exploit variation in migration flows, wages, and distributions of daily temperature. We begin with the expected lifetime utility of a household in region n and sector k in equation (5), which may alternatively be expressed as:

$$V_{n,t}^{k} = \underbrace{U\left(C_{n,t}^{k}, B_{n,t}\right)}_{\text{instantaneous utility}} + \underbrace{\beta(V_{n,t+1}^{k})}_{\text{base value staying in market}} + \underbrace{\mathbb{E}_{\epsilon}\left[\max_{\{i,s\}_{i=1,s=0}^{N,K}} \left\{\nu\epsilon_{i,t}^{s} + \nu\bar{\epsilon}_{ni,t}^{ks}\right\}\right]}_{\text{option value of moving markets}} \tag{26}$$

where $V_{n,t}^{k} \equiv \mathbb{E}_{\epsilon}\left[v_{n,t}^{k}\right]$ and:

$$\bar{\epsilon}_{ni,t}^{ks} \equiv \frac{1}{\nu}\left[\beta\left(V_{i,t+1}^{s} - V_{n,t+1}^{k}\right) - \mu_{ni}^{ks}\right] \tag{27}$$

represents the value of moving from (n,k) to (i,s), net of moving costs.

Equation (27) is analogously the difference in idiosyncratic shocks $\epsilon_{n,t}^{k} - \epsilon_{i,t}^{s}$ at which a worker in market (n,k) is indifferent between staying in the same market and moving to market (i,s). Rearranging this equation and substituting in the expected lifetime utilities from equation (26) yields the Euler equation:

$$\begin{aligned}
\nu\bar{\epsilon}_{ni,t}^{ks} + \mu_{ni}^{ks} &= \beta\left(V_{i,t+1}^{s} - V_{n,t+1}^{k}\right) \\
&= \beta\left[U(C_{i,t+1}^{s}, B_{i,t+1}) - U(C_{n,t+1}^{k}, B_{n,t+1}) + \mathbb{E}_{t+1}\left(V_{i,t+2}^{s} - V_{n,t+2}^{k}\right) + \Omega(\bar{\epsilon}_{\mathbf{i,t+1}}^{\mathbf{s}}) - \Omega(\bar{\epsilon}_{\mathbf{n,t+1}}^{\mathbf{k}})\right] \\
&= \beta\left[U(C_{i,t+1}^{s}, B_{i,t+1}) - U(C_{n,t+1}^{k}, B_{n,t+1}) + \nu\bar{\epsilon}_{ni,t+1}^{ks} + \mu_{ni}^{ks} + \Omega(\bar{\epsilon}_{\mathbf{i,t+1}}^{\mathbf{s}}) - \Omega(\bar{\epsilon}_{\mathbf{n,t+1}}^{\mathbf{k}})\right]
\end{aligned} \tag{28}$$

where:

$$\begin{aligned}
\Omega(\bar{\epsilon}_{\mathbf{n,t}}^{\mathbf{k}}) &\equiv \mathbb{E}_{\epsilon}\left[\max_{\{i,s\}_{i=1,s=0}^{N,K}} \left\{\nu\epsilon_{i,t}^{s} + \nu\bar{\epsilon}_{ni,t}^{ks}\right\}\right] \\
&= \sum_{i=1}^{N}\sum_{s=0}^{K}\int_{-\infty}^{\infty}\left(\nu\epsilon_{i,t}^{s} + \nu\bar{\epsilon}_{ni,t}^{ks}\right)\left(f\left(\epsilon_{i,t}^{s}\right)\prod_{lh\neq is} F\left(\epsilon_{i,t}^{s} + \bar{\epsilon}_{ni,t}^{ks} - \bar{\epsilon}_{nl,t}^{kh}\right)\right) d\epsilon_{i,t}^{s} \\
&= \nu\log\left(\sum_{i=1}^{N}\sum_{s=0}^{K}\exp\left[\left(\beta\left(V_{i,t+1}^{s} - V_{n,t+1}^{k}\right) - \mu_{ni}^{ks}\right)/\nu\right]\right).
\end{aligned}$$

Note that the last equality follows from the properties of the Type 1 Extreme Value distribution. $\Omega(\bar{\epsilon}_{\mathbf{n,t}}^{\mathbf{k}})$ captures the option value of being able to move from market (n,k).

As in Artuc et al. (2010), the Euler equation given by equation (28) tells us that the future benefits for the marginal mover at time t (left hand side) are composed of the discounted expected difference in one period ahead flow utilities, the future benefits from the perspective of time $t+1$, and the difference in future option values.

We now show that the option value of moving markets $\Omega(\bar{\epsilon}_{\mathbf{n,t}}^{\mathbf{k}})$ and the expected continuation value from moving $\bar{\epsilon}_{ni,t}^{ks}$ can be expressed as functions of only migration shares. Recall that the migration shares are given by equation (6):

$$\pi_{ni,t}^{ks} = \frac{\exp\left[\left(\beta V_{i,t+1}^{s} - \mu_{ni}^{ks}\right)/\nu\right]}{\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta V_{l,t+1}^{h} - \mu_{nl}^{kh}\right)/\nu\right]}$$

Thus the share of workers who remained in the same market (n,k) at time t is given by:

$$\pi_{nn,t}^{kk} = \frac{\exp\left[\left(\beta V_{n,t+1}^{k}\right)/\nu\right]}{\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta V_{l,t+1}^{h} - \mu_{nl}^{kh}\right)/\nu\right]}.$$

Taking logs, we obtain:

$$\begin{aligned} \log \pi_{nn,t}^{kk} &= \frac{1}{\nu}\beta V_{n,t+1}^{k} - \log \sum_{l=1}^{N}\sum_{h=o}^{K}\exp\left[\left(\beta V_{l,t+1}^{h} - \mu_{nl}^{kh}\right)/\nu\right] \\ \implies -\nu \log \pi_{nn,t}^{kk} &= \nu \log\left(\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta\left(V_{l,t+1}^{h} - V_{n,t+1}^{k}\right) - \mu_{nl}^{kh}\right)/\nu\right]\right) \equiv \Omega(\bar{\epsilon}_{\mathbf{n,t}}^{\mathbf{k}}). \end{aligned} \tag{29}$$

The option value of market (n,k) is simply the negative log share of households who stay, scaled by the migration elasticity. Taking logs of the ratio of migration shares against the share of workers who remain in the same market, $\bar{\epsilon}_{ni,t}^{ks}$ can then be expressed as:

$$\log\left(\frac{\pi_{ni,t}^{ks}}{\pi_{nn,t}^{kk}}\right) = \frac{\beta}{\nu}\left(V_{i,t+1}^{s} - V_{n,t+1}^{k}\right) - \frac{\mu_{ni}^{ks}}{\nu} \equiv \bar{\epsilon}_{ni,t}^{ks}. \tag{30}$$

Finally, we derive the moment condition by substituting the expressions for $\Omega(\bar{\epsilon}_{\mathbf{n,t}}^{\mathbf{k}})$ and $\bar{\epsilon}_{ni,t}^{ks}$, given by equations (29) and (30) respectively, into the Euler equation in equation (28):

$$\begin{aligned} &\nu\bar{\epsilon}_{ni,t}^{ks} + \mu_{ni}^{ks} = \beta\left[U(C_{i,t+1}^{s}, B_{i,t+1}) - U(C_{n,t+1}^{k}, B_{n,t+1}) + \nu\bar{\epsilon}_{ni,t+1}^{ks} + \mu_{ni}^{ks} + \Omega(\bar{\epsilon}_{\mathbf{i,t+1}}^{\mathbf{s}}) - \Omega(\bar{\epsilon}_{\mathbf{n,t+1}}^{\mathbf{k}})\right] \\ &\implies \nu \log\left(\frac{\pi_{ni,t}^{ks}}{\pi_{nn,t}^{kk}}\right) + \mu_{ni}^{ks} = \beta\left[\log\left(\frac{B_{i,t+1}}{B_{n,t+1}}\frac{C_{i,t+1}^{s}}{C_{n,t+1}^{k}}\right) + \nu\log\left(\frac{\pi_{ni,t+1}^{ks}}{\pi_{nn,t+1}^{kk}}\right) + \mu_{ni}^{ks} + \nu\log\left(\frac{\pi_{nn,t+1}^{kk}}{\pi_{ii,t+1}^{ss}}\right)\right] \\ &\implies \left[\frac{\beta}{\nu}\log\left(\frac{B_{i,t+1}}{B_{n,t+1}}\frac{C_{i,t+1}^{s}}{C_{n,t+1}^{k}}\right) + \beta\log\left(\frac{\pi_{ni,t+1}^{ks}}{\pi_{ii,t+1}^{ss}}\right) - \log\left(\frac{\pi_{ni,t}^{ks}}{\pi_{nn,t}^{kk}}\right) + \frac{\beta-1}{\nu}\mu_{ni}^{ks}\right] = 0. \end{aligned}$$

Assuming perfect information, using equation (1) to substitute in for the B terms, and rearranging delivers equation (19) in the paper.

D.3 Do Space and Dynamics Matter for Response Function Estimation?

Here we estimate partial equilibrium, static analogues of our response function estimators and provide intuition for how they are biased. The comparison of response functions will be from within the same class of models and using the same weather and economic data, but under different assumptions on how markets are spatially linked, and how households are forward-looking.

Spatial Bias in GDP Impacts The literature often motivates productivity specifications with a partial equilibrium model of production (Dell et al., 2012; Burke et al., 2015; Nath, 2020). A simple Cobb-Douglas version of the model would be:

$$Y_{it} = a_{it} L_{it}^{\gamma} K_{it}^{(1-\gamma)}$$

where $a_{it} = \bar{a}_{it} \exp(f(T_{it};\beta))$ is total factor productivity inclusive of temperature effects, L_{it} is labor, K_{it} is capital, and $\gamma \in [0,1]$. Taking the log of both sides and rearranging we obtain:

$$\log \frac{Y_{it}}{L_{it}} = f(T_{it};\beta) + \log \bar{a}_{it} + (1-\gamma) \log \frac{1-\gamma}{\gamma}$$

where the last term is constant and captures the capital to labor ratio $(1-\gamma)/\gamma$ in equilibrium. Thus, regressing GDP per capita on a function of temperature and unit and time fixed effects to absorb $\bar{a}_{it}$ can identify the effect of temperature on productivity under the assumption that the remaining variation in temperature is not correlated with the error term.

How does this compare to the analogous GDP specification generated by our general equilibrium model? The equilibrium conditions of our model show that GDP can be written as:

$$\log\left(Y_{n,t}^k\right) = g(\mathbf{T}_{n,t};\zeta_{\mathbf{Z}}^k) + -\theta^k \log\left(x_{n,t}^k\right) - \theta^k \log\left(\Lambda_{n,t}^k\right). \tag{31}$$

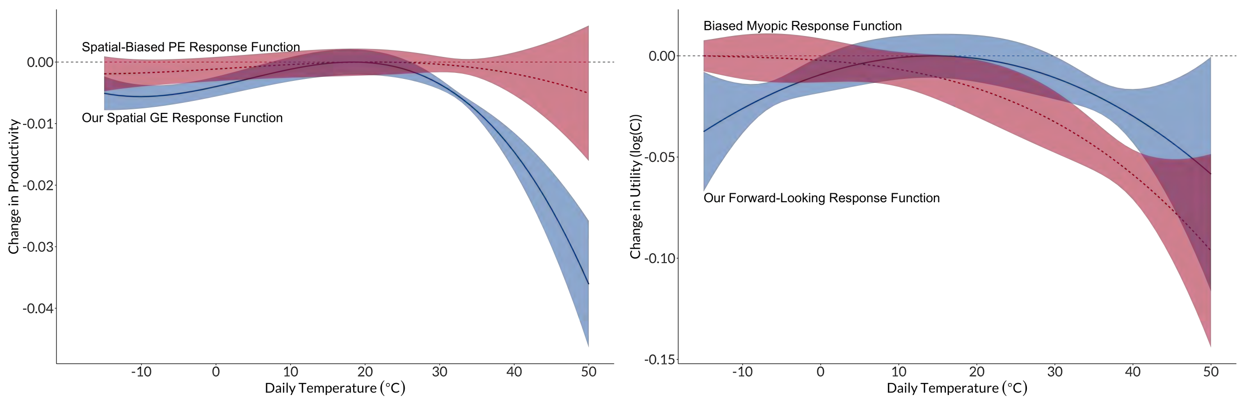
GDP is a function of productivity, input costs, and firm market access $\Lambda_{n,t}^{-\theta^k}$. The important term here for identification in spatial equilibrium is firm market access:

$$\Lambda_{n,t}^{-\theta^k} \equiv \sum_{i=1}^{N} \frac{(\tau_{in,t})^{-\theta^k} X_{i,t}}{\sum_{l=1}^{N} Z_{l,t}^k \left(x_{l,t}^k \tau_{il,t}^k\right)^{-\theta^k}}.$$

Firm market access is a multilateral term that is a function of *all* countries' productivities, and thus all countries' temperature distributions. Intuitively, inputs and consumption goods are sourced from multiple markets and thus temperature shocks to other markets can propagate across industries and regional borders and affect GDP in (n,k).

The central identification issue arises because temperature is positively correlated across space and this multilateral market access term is omitted and relegated to the error term of partial

Figure D.1: The effect of daily temperature on productivity using the GDP regression approach versus our spatial general equilibrium approach (left) and on amenities using a dynamic versus static approach (right).



Left: Our estimated productivity response function and a partial equilibrium analogue productivity response function. The response functions are constructed using a third-degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are winsorized at -15°C and 50°C. The solid response function is the same as in the left panel of Figure 2. The dashed response function is from the GDP regression in equation (32). The GDP estimating equation includes industry-country and industry-year fixed effects. Standard errors are clustered at the country level.
Right: Our forward-looking amenity response function and a myopic analogue productivity response function. The response functions are constructed using a third-degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are winsorized at -15°C and 50°C. The solid response function is the same as in the right panel of Figure 2. The dashed response function is from the static regression in equation (33). The static estimating equation includes origin-destination-industry and industry-year fixed effects. Standard errors are clustered two ways at the origin and destination levels.

equilibrium specifications. Notice that n's market access term contains productivity for all other regions l: $Z_{l,t}^k$. Productivity in l is a function of l's temperature, which is also implicitly in the error term, but also correlated with our variable of interest because temperature is positively spatially correlated. These partial equilibrium approaches thus suffer from omitted variable bias.

Does this bias matter? The left panel of Figure D.1 plots in red the estimated response function from the following specification:

$$\log\left(Y_{n,t}^k\right) = g(\mathbf{T}_{n,t}; \zeta_{\mathbf{Z}}^k) + \zeta_{\mathbf{X}}\mathbf{X_t} + \delta_t^k + \phi_n^k + \varepsilon_{n,t}^k \tag{32}$$

where δ_t^k is an industry-year effect and ϕ_n^k is an industry-region effect, and the estimating equation specifically omits market potential as a regressor. The primary difference between this specification and the literature is that our model delivers an equation in terms of GDP not GDP per capita because of the structure of our model.

The biased response function shows sensitivity to extreme heat and cold. There are, however, two key differences compared to our preferred response function in blue which matches Figure 2.

First, the red response function is shifted right and peaks several degrees higher. Second, it is significantly flatter. In our setting, the bias from ignoring spatial linkages in the economy tends to understate the costs of extreme temperature. Why is this the case? Consider an example where one day of the year in each region is 30°C instead of 20°C. Our general equilibrium consistent response function shows that this will tend to decrease productivity in each region. The issue for equation (31) is that this increases n's market access because n's competitors now have lower productivity. Greater market access increases GDP so the error term will be positively correlated with n's temperature shock. By omitting market access from the estimating equation, we are attributing this effect to own-temperature and it gets picked up by our empirical estimates $\widehat{\zeta}^k_{\mathbf{Z}}$. Since the effect on GDP through market access is positive, the bias tends to flatten out the response function and lead to underestimates of the negative impacts of temperature extremes on productivity.

Myopia Bias in Amenities Next we demonstrate that accounting for dynamics and forward-looking behavior significantly affects our amenity response function. Because of the timing of the household problem where decisions are at the end of a period, we define a myopic household as only caring about the immediate change in flow payoff at time $t+1$ caused by their time t moving decision, but not any effects beyond $t+1$. With a myopic household we obtain following estimating equation:

$$\log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) = \frac{1}{\nu}\left[f(\mathbf{T_{i,t+1}};\zeta_{\mathbf{B}}) - f(\mathbf{T_{n,t+1}};\zeta_{\mathbf{B}})\right] + \frac{1}{\nu}\log\left(\frac{\omega^s_{i,t+1}}{\omega^k_{n,t+1}}\right) + \delta^k_t + \varphi^k_{ni} + \varepsilon^{ks}_{ni,t} \tag{33}$$

Since the household is myopic, the household only cares about differences in flow payoffs, and not continuation values captured by future migration. The right panel of Figure D.1 shows the amenity response function from the myopic model as a dashed line, and from our forward-looking model in the main text as a solid line.

In our setting, ignoring forward-looking behavior shifts the response function to the left. Statistically, this arises because (1) temperature differences are strongly positively correlated over time, and (2) current temperature differences tend to be negatively correlated with future real wages differences. These two facts about the data indicate that current temperature differences are negatively correlated with future payoffs, captured by the future migration flows in equation (20). Since the myopic regression omits the future migration flows terms and temperatures are rising over time, the correlated negative shocks to future payoffs through amenities and wages are picked up by the current temperature term. Therefore, the myopic response function tends to overstate the negative effects of future warming and works to shift the response function to the left.

The economic intuition for this finding through the temperature channel is that forward-looking households are likely to move to locations that are cooler than they prefer, understanding that there will be additional warming over time and there are costs to moving. The myopic regression mistakenly attributes this to the households preferring colder temperatures.

E Welfare Computation, Decomposition, and Derivations

In this appendix we provide a more detailed analytical welfare decomposition and show how to compute welfare for the simulations when we constrain mobility trajectories.

E.1 Welfare Decomposition

Recall from equation (21) in the paper that the consumption-equivalent change in welfare can be computed using relative time difference variables:

$$\log\left(\delta_n^k\right) = \sum_{t=1}^{\infty} \beta^l \log\left(\widehat{B_{n,t}} \frac{\widehat{C_{n,t}^k}}{\left(\widehat{\pi_{nn,t}^{kk}}\right)^{\nu}}\right) = \sum_{t=1}^{\infty} \beta^t \left[\underbrace{\log \widehat{B_{n,t}}}_{\substack{\text{direct climate}\\\text{impact on}\\\text{amenities}}} \underbrace{- \nu \log \widehat{\pi_{nn,t}^{kk}}}_{\substack{\text{changes in}\\\text{option value}}} + \underbrace{\log \widehat{w_{n,t}^k} - \log \widehat{P_{n,t}}}_{\text{changes in real wages}}\right].$$

The first two terms capture climate impacts on utility, while the last term captures climate impacts on production. We can then decompose welfare into a set of exogenous and endogenous components:

$$\log \widehat{w_{n,t}^k} = \log \frac{\widehat{Y_{n,t}^k}}{\widehat{L_{n,t}^k}} = \underbrace{\log \widehat{Z_{n,t}^k}}_{\substack{\text{direct climate}\\\text{impact on}\\\text{productivity}}} \underbrace{- \theta^k \log \widehat{x_{i,t}^k}}_{\substack{\text{changes in}\\\text{input costs}}} - \underbrace{\theta^k \log \widehat{\Lambda_n}}_{\substack{\text{changes}\\\text{in firm}\\\text{market access}}} - \underbrace{\log \widehat{L^{n,t}}}_{\substack{\text{changes in}\\\text{labor}\\\text{competition}}} \tag{34}$$

$$\log \widehat{P_{n,t}} = \log\left(\prod_{s=1}^{K} (\widehat{P_{n,t}^s})^{\alpha^s}\right) = \sum_{s=1}^{K} \alpha^s \log \widehat{P_{n,t}^s} = \underbrace{-\sum_{s=1}^{K} \frac{\alpha^s}{\theta^s} \log \widehat{\Phi_{n,t}^s}}_{\substack{\text{changes in consumer}\\\text{market access}}} \tag{35}$$

where $\widehat{Y_{n,t}^k} \equiv \sum_{i=1}^N \lambda_{in,t} X_{i,t}$, $\Lambda_{n,t}^{-\theta^k} \equiv \sum_{i=1}^N \frac{(\tau_{in,t})^{-\theta^k} X_{i,t}}{\Phi_{i,t}^k}$, and $\Phi_{i,t}^k \equiv \sum_{l=1}^N Z_{l,t}^k \left(x_{l,t}^k \tau_{il,t}^k\right)^{-\theta^k}$.

The terms in equations (21) and (34)-(35) highlight the different spatial channels in which climate shocks are transmitted through our economy, as well as the role of different adaptation mechanisms. For example, welfare changes from amenities are caused by exogenous changes in local temperature, while welfare changes from nominal wages are driven by exogenous productivity changes, and endogenous changes in prices and labor allocation. Note that changes in endogenous wages and prices capture contemporaneous adaptation channels, while changes in option value capture the dynamic adaptation channel of migration across labor markets.

We omit the proof for the first level of the welfare decomposition, as seen in equation (21) given its similarity to CDP. The decomposition of changes in wages (equation 34) can be derived as follows. From the labor market clearing condition (equation 15), we have that:

$$w_{n,t}^{k} L_{n,t}^{k} = \gamma_{n}^{k}\left(1-\psi^{k}\right) Y_{n,t}^{k}$$

where $Y_{n,t}^{k} \equiv \sum_{i=1}^{N} \lambda_{in,t} X_{i,t} = \sum_{i=1}^{N} X_{in,t}$. Expressing this condition in terms of counterfactual changes, we obtain:

$$\widehat{w}_{n,t}^{k} = \frac{\widehat{Y}_{n,t}^{k}}{\widehat{L}_{n,t}^{k}}.$$

Now note that from the expression for trade shares from equation (12) we have:

$$Y_{n,t}^{k} = \sum_{i=1}^{N} \lambda_{in,t} X_{i,t} = \sum_{i=1}^{N} \frac{Z_{n,t}^{k}\left(x_{n,t}^{k}\tau_{in,t}^{k}\right)^{-\theta^{k}} X_{i,t}}{\sum_{l} Z_{l,t}^{k}\left(x_{l,t}^{k}\tau_{il,t}^{k}\right)^{-\theta^{k}}} = Z_{n,t}^{k}\left(x_{n,t}^{k}\right)^{-\theta^{k}} \sum_{i=1}^{N} \frac{\left(\tau_{in,t}^{k}\right)^{-\theta^{k}} X_{i,t}}{\sum_{l} Z_{l,t}^{k}\left(x_{l,t}^{k}\tau_{il,t}^{k}\right)^{-\theta^{k}}}.$$

Defining $\Lambda_{n,t}^{-\theta^{k}} \equiv \sum_{i=1}^{N} \frac{(\tau_{in,t})^{-\theta^{k}} X_{i,t}}{\Phi_{i,t}^{k}}$ where $\Phi_{i,t}^{k} \equiv \sum_{l=1}^{N} Z_{l,t}^{k}\left(x_{l,t}^{k}\tau_{il,t}^{k}\right)^{-\theta^{k}}$, we thus have that:

$$\log \widehat{w}_{n,t}^{k} = \log \widehat{Y}_{n,t}^{k} - \log \widehat{L}_{n,t}^{k} = \log \widehat{Z_{n,t}^{k}} - \theta^{k} \log \widehat{x_{i,t}^{k}} - \theta^{k} \log \widehat{\Lambda_{n}} - \log \widehat{L_{n,t}}.$$

The decomposition for price changes (equation 35) is straightforward. Expressing the price index in each region, given by equation (3), in counterfactual changes, we have:

$$\log \widehat{P_{n,t}} = \log\left(\prod_{s=1}^{K}\left(\widehat{P_{n,t}^{s}}\right)^{\alpha^{s}}\right) = \sum_{s=1}^{K} \alpha^{s} \log \widehat{P_{n,t}^{s}}.$$

Expressing the price index for each market from equation (13) in counterfactual changes and using the definition of $\Phi_{n,t}^{s}$, we have:

$$\widehat{P_{n,t}^{s}} = \left(\widehat{\Phi_{n,t}^{s}}\right)^{-1/\theta^{s}}.$$

Combining both equations above yields:

$$\log \widehat{P_{n,t}} = -\sum_{s=1}^{K} \frac{\alpha^{s}}{\theta^{s}} \log \widehat{\Phi_{n,t}^{s}},$$

.

E.2 Derivation of Constrained Welfare

The welfare computation in Section 2.5 of the paper will not be correct for the cases when we constrain mobility trajectories. The intuition is that the welfare derivation inverts the expression for migration shares, which rely upon households optimally choosing their locations without constraints. When migration shares are constrained, they no longer will reflect the relative (option) values across locations, and thus we can't simply sum up changes in utility in the location and adjust for the option value using the own-migration share.

Here we show how to compute welfare when migration shares under climate change are fixed to their trajectory without climate change. The intuition is that constraining the climate change migration trajectories to exactly match the no climate change trajectories results in both simulations incurring the exact same mobility costs so they drop out of the welfare derivation. This allows us to simply sum up the differences in flows of utility over time for households in each location.

To begin, start with the representative household's problem:

$$\begin{aligned} V_{n,t}^k = & \max_{\{\pi_{ni,t}^{ks}\}_{i=1,s=0}^{N,K}} U_{n,t}^k + \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks}\left[\beta V_{i,t+1}^s - \mu_{ni}^{ks}\right] - \nu \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks} \log \pi_{ni,t}^{ks} \\ & \text{s.t} \quad \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks} = 1, \qquad 0 < \pi_{ni,t}^{ks} \leq 1 \quad \forall\, n, i, k, s, t. \end{aligned}$$

In our constrained case we are fixing $\pi_{ni,t}^{ks}$ in the simulation with climate change so we can simply rewrite the constrained welfare under climate change as:

$$V_{n,t}^k = U_{n,t}^k + \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks\,\prime}\left[\beta V_{i,t+1}^s - \mu_{ni}^{ks}\right] - \nu \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks\,\prime} \log \pi_{ni,t}^{ks\,\prime} \tag{36}$$

where primes indicate quantities from the no climate change simulation. Our equivalent variation welfare measure is $\log \delta_n^k$ in utility terms and is defined by:

$$\begin{aligned} \sum_{t=0}^{T} \beta^t \log \delta_n^k &= \left[V_{n,t}^k - V_{n,t}^{k\,\prime}\right] \\ &= \left[\left(U_{n,t}^k + \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks\,\prime} \beta V_{i,t+1}^s\right) - \left(U_{n,t}^{k\,\prime} + \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks\,\prime} \beta V_{i,t+1}^{s\,\prime}\right)\right] \end{aligned}$$

where migration costs and the quasi-love-of-variety expression cancel because the migration share terms are identical in the baseline and counterfactual. Next, collect like terms:

$$\left[V_{n,t}^k - V_{n,t}^{k\,\prime}\right] = \left[\left(U_{n,t}^k - U_{n,t}^{k\,\prime}\right) + \beta \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks\,\prime}\left[V_{i,t+1}^s - V_{i,t+1}^{s\,\prime}\right]\right].$$

We can then continually substitute the left hand side into the right hand side to get an infinite sum. At time $t = 0$ we have that the difference in welfare is:

$$
\begin{aligned}
\left[v_{n,0}^{k} - {v_{n,0}^{k}}'\right] = & \left(U_{n,0}^{k} - {U_{n,0}^{k}}'\right) \\
& + \beta \sum_{i=1}^{N} \sum_{s=0}^{K} {\pi_{ni,t}^{ks}}' \left[U_{i,1}^{s} - {U_{i,1}^{s}}'\right] \\
& + \beta^{2} \sum_{j=1}^{N} \sum_{w=0}^{K} {\pi_{ni,t}^{ks}}' {\pi_{ij,t+1}^{sw}}' \left[U_{j,2}^{w} - {U_{j,2}^{w}}'\right] \\
& + \beta^{3} \sum_{l=1}^{N} \sum_{v=0}^{K} {\pi_{ni,t}^{ks}}' {\pi_{ij,t+1}^{sw}}' {\pi_{jl,t}^{wv}}' \left[U_{l,3}^{v} - {U_{l,3}^{v}}'\right] \\
& + \ldots
\end{aligned}
\tag{37}
$$

The difference in time $t = 0$ welfare is the the discounted stream of weighted average flow payoffs across markets, where the weights are the shares of the initial population that moves to each location at that future time.

Next, we need to compute the difference in flow utilities in each market and time. We can write the difference in flow utilities between the baseline and counterfactual using data from the simulations as:

$$
\begin{aligned}
U_{n,0}^{k} - {U_{n,0}^{k}}' &= \log \frac{C_{n,0}^{k} B_{n,0}^{k}}{{C_{n,0}^{k}}' {B_{n,0}^{k}}'} = \frac{B_{n,0}^{k}}{{B_{n,0}^{k}}'} \\
U_{n,1}^{k} - {U_{n,1}^{k}}' &= \log \frac{C_{n,1}^{k} B_{n,1}^{k}}{{C_{n,1}^{k}}' {B_{n,1}^{k}}'} = \log \frac{C_{n,0}^{k} \dot{C}_{n,1}^{k} B_{n,0}^{k} \dot{B}_{n,1}^{k}}{{C_{n,0}^{k}}' {\dot{C}_{n,1}^{k}}' {B_{n,0}^{k}}' {\dot{B}_{n,1}^{k}}'} = \log \frac{\dot{C}_{n,1}^{k} B_{n,0}^{k} \dot{B}_{n,1}^{k}}{{\dot{C}_{n,1}^{k}}' {B_{n,0}^{k}}' {\dot{B}_{n,1}^{k}}'} \\
U_{n,t}^{k} - {U_{n,t}^{k}}' &= \log \frac{C_{n,t}^{k} B_{n,t}^{k}}{{C_{n,t}^{k}}' {B_{n,t}^{k}}'} = \log \frac{C_{n,0}^{k} B_{n,0}^{k} \prod_{s=1}^{t} \dot{C}_{n,s}^{k} \dot{B}_{n,s}^{k}}{{C_{n,0}^{k}}' {B_{n,0}^{k}}' \prod_{s=1}^{t} {\dot{C}_{n,s}^{k}}' {\dot{B}_{n,s}^{k}}'} = \log \frac{\prod_{s=1}^{t} \dot{C}_{n,s}^{k} \dot{B}_{n,s}^{k}}{\prod_{s=1}^{t} {\dot{C}_{n,s}^{k}}' {\dot{B}_{n,s}^{k}}'}.
\end{aligned}
$$

Where $\dot{C}_{n,t}^{k}$ is the change in real wage at time t, ${\dot{B}_{n,t}^{k}}'$ is constant since we are holding the temperature distribution constant in the no climate change counterfactual and we are assuming non-climate amenities are constant, $\dot{B}_{n,t}^{k}$ is just the difference in the temperature shock to amenities between $t-1$ and t, $\frac{C_{n,0}^{k}}{{C_{n,0}^{k}}'} = 1$ since the initial allocation and thus flow consumption is identical, and $\frac{B_{n,0}^{k}}{{B_{n,0}^{k}}'} = 1$ since we assume the counterfactual temperature distribution for all years is the initial year 2015 temperature distribution.

Define $\tilde{U}_{n,t}^{k} \coloneqq U_{n,t}^{k} - {U_{n,t}^{k}}'$. Let $\tilde{\mathbf{U}}_{\mathbf{t}}$ be the vector of $\tilde{U}_{n,t}^{k}$ terms, let $\mathbf{log}\,\boldsymbol{\delta}$ be the vector of $\log \delta_{n}^{k}$ terms, and let $\boldsymbol{\pi}_{\boldsymbol{t}}'$ be the $NK \times NK$ transition matrix of $\pi_{ni,t}^{ks}$ terms. In vector notation we then have the welfare effect is:

$$
\mathbf{log}\,\boldsymbol{\delta} = \frac{1}{\sum_{t=0}^{T} \beta^{t}} \left[\sum_{t=1}^{T} \beta^{t} \left(\prod_{s=1}^{t} \boldsymbol{\pi}_{\boldsymbol{s}}'\right) \tilde{\mathbf{U}}_{\mathbf{t}}\right]. \tag{38}
$$

All variables on the right hand side are parameters (β) or results from the simulations.

F Simulating and Decomposing the Impacts of Climate Change

In this appendix we provide details on how we simulate our full model to compute the welfare impacts of climate change, and how we simulate our model with different combinations of adaptation channels fixed to quantify their value and distributional effects.

F.1 Expressing and Solving the Model in Time Changes

Our first step is to express the model in time changes using hat algebra as in CDP. This transformation allows us to simulate the baseline economy and solve for counterfactual changes in the economy without knowing the levels of the time-invariant exogenous fundamentals $\bar{\Theta} = \{b, \mu, H\}$. In what follows, we denote $\dot{Y}_{t+1} \equiv \frac{Y_{t+1}}{Y_t}$ to represent proportional time changes between time periods t and $t+1$. We first express the production side of our economy in time changes following CDP:

Proposition 3 (CDP)**.** *Given the allocation of the momentary equilibrium at* $t, \{L_t, \lambda_t, X_t\}$ *, the solution to the momentary equilibrium at* $t+1$ *for a given change in* $\dot{L}_{t+1}$ *and* $\dot{\Theta}_{t+1}$ *does not require information on the level of fundamentals at* t*,* Θ_t*, or* $\bar{\Theta}$*. In particular, it is obtained as the solution to the following system of nonlinear equations:*

$$\dot{x}^k_{n,t+1} = \left(\dot{L}^k_{n,t+1}\right)^{\gamma^k_n \psi_n} \left(\dot{w}^k_{n,t+1}\right)^{\gamma^k_n} \prod_{s=1}^{K} \left(\dot{P}^k_{n,t+1}\right)^{\gamma^{ks}_n} \tag{39}$$

$$\dot{P}^k_{n,t+1} = \left[\sum_{i=1}^{N} \lambda^k_{ni,t} \dot{Z}^k_{i,t+1} \left(\dot{x}^k_{i,t+1} \dot{\tau}^k_{ni,t+1}\right)^{-\theta^k}\right]^{\frac{1}{\theta^k}} \tag{40}$$

$$\dot{\lambda}^k_{ni,t+1} = \left(\frac{\dot{x}^k_{n,t+1} \dot{\tau}^k_{ni,t+1}}{\dot{P}^k_{n,t+1}}\right)^{-\theta^k} \dot{Z}^k_{n,t+1} \tag{41}$$

$$X^k_{n,t+1} = \sum_{s=1}^{K} \gamma^{ks}_n \sum_{i=1}^{N} \lambda^k_{in,t+1} X^k_{i,t+1} + \alpha^k \left(\sum_{k=1}^{K} w^k_{n,t+1} L^k_{n,t+1} + \iota_n \chi_{t+1}\right) \tag{42}$$

$$w^k_{n,t+1} L^k_{n,t+1} = \gamma^k_n \left(1 - \psi^k\right) \sum_{i=1}^{N} \lambda^k_{in,t+1} X^k_{i,t+1} \tag{43}$$

for all regions n *and* i*, industries* k *and* s *at each time* t*, where* $\chi_{t+1} = \sum_{i=1}^{N} \sum_{s=1}^{K} \frac{\psi_i}{1-\psi_i} w^s_{i,t+1} L^s_{i,t+1}$ *and the exogenous time changes in productivities* $\dot{Z}_{t+1}$ *are given by equation* (11)*.*

Once we have the momentary equilibrium (i.e. production side of the economy) at each t using Proposition 3, we express the household side of the economy in time differences with the next proposition from CDP:

Proposition 4 (CDP)**.** *Define* $u^k_{n,t} \equiv \exp(V^k_{n,t})$. *Given an initial allocation of the economy,* $(L_0, \pi_0, X_0, \pi_{-1})$ *and an anticipated convergent sequence of time changes in fundamentals,* $\{\dot{\mathbf{\Theta}}_{\mathbf{t}}\}_{t=1}^{\infty}$ *with* $\lim_{t\to\infty} \dot{\mathbf{\Theta}}_{\mathbf{t}} = 1$, *the solution to the sequential competitive equilibrium in time differences does not require information on the level of the fundamentals,* $\{\mathbf{\Theta}_{\mathbf{t}}\}_{t=0}^{\infty}$ *or* $\overline{\mathbf{\Theta}}$. *In particular, it is obtained as the solution to the following system of nonlinear equations:*

$$\dot{\pi}^{ks}_{ni,t+1} = \frac{\left(\dot{u}^s_{i,t+2}\right)^{\beta/\nu}}{\sum_{l=1}^N \sum_{h=0}^K \pi^{kh}_{nl,t} \left(\dot{u}^h_{l,t+2}\right)^{\beta/\nu}} \tag{44}$$

$$\dot{u}^k_{n,t+1} = \dot{B}_{n,t+1} \dot{\omega}^k_n(\dot{L}_{t+1}, \dot{Z}_{t+1}, \dot{\kappa}_{t+1}) \left(\sum_{i=1}^N \sum_{s=0}^K \pi^{ks}_{ni,t} \left(\dot{u}^s_{i,t+2}\right)^{\beta/\nu} \right)^{\nu} \tag{45}$$

$$L^k_{n,t+1} = \sum_{i=1}^N \sum_{s=0}^K \pi^{sk}_{in,t} L^s_{i,t} \tag{46}$$

for all regions n *and* i, *industries* k *and* s *at each time* t, *where* $\{\dot{\omega}^k_n(\dot{L}_t, \dot{Z}_t, \dot{\kappa}_t)\}_{n=1,k=0,t=1}^{N,K,\infty}$ *is the sequence of real wages that solves the momentary equilibrium at each* t *given* $\{\dot{L}_{t+1}, \dot{Z}_{t+1}, \dot{\kappa}_{t+1}\}_{t=1}^{\infty}$, *and the exogenous time changes in amenities are given by the time changes of equation* (1), *namely:* $\dot{B}_{n,t+1} = \dot{\bar{B}}_{n,t+1} \exp\left(f(\mathbf{T}_{n,t+1}; \gamma) - f(\mathbf{T}_{n,t}; \gamma)\right)$.

Given these propositions, we outline the numerical algorithm for solving the model in time changes. In particular, Proposition 3 shows us how to solve the momentary equilibrium at each t in time differences given the equilibrium in the previous period, which forms the inner loop of the numerical algorithm. The specific steps drawn from CDP are as follows:

- **Step 1**: For each $t \geq 0$, given $\dot{L}^k_{n,t+1}$ from the labor supply decision in the outer loop (described below), guess a value for $\dot{w}^{k(0)}_{n,t+1}$ where the superscript (0) indicates it is a guess.

- **Step 2**: Solve for prices $\dot{P}^k_{n,t+1}$ using equation (39) and (40) by looping over guesses for $\dot{P}^k_{n,t+1}$. Specifically, for each guess of $\dot{P}^k_{n,t+1}$, obtain $\dot{x}^k_{n,t+1}$ from equation (39) and check whether the value of $\dot{P}^k_{n,t+1}$ from equation (40) is close to the guess. Update the guess of $\dot{P}^k_{n,t+1}$ and repeat till a suitable pre-specified tolerance level is met.

- **Step 3**: Use equation (41) and $\dot{P}^k_{n,t+1}$ to obtain $\lambda^k_{ni,t+1}$.

- **Step 4**: Use equation (42), $\lambda^k_{ni,t+1}$, the current guess $\dot{w}^{k(0)}_{n,t+1}$, and $\dot{L}^k_{n,t+1}$ (given by the outer loop) to obtain $X^k_{n,t+1}$.

- **Step 5**: Use equation (43), $X^k_{n,t+1}$, and $\dot{L}^k_{n,t+1}$ (from the outer loop) to obtain a value for $\dot{w}^{k(1)}_{n,t+1}$. Check this value against the initial guess. If it is within a pre-specified tolerance level, the momentary equilibrium at time t is solved. Otherwise, update the guess for $\dot{w}^k_{n,t+1}$ and return to Step 1.

- **Step 6**: Repeat Steps 1-5 for every period t to obtain the trajectories for wages and prices $\{\dot{w}^k_{n,t+1}, \dot{P}^k_{n,t+1}\}^T_{t=0}$ i.e. solve the momentary equilibrium for all t.

Given how to solve the momentary equilibrium or production side of the economy at each t in time differences, we then use Proposition 4 to solve for the outer loop of the economy numerically (changes to CDP algorithm in bold):

- **Step 1**: Guess a path of $\{\dot{u}^{k(0)}_{n,t+1}\}^T_{t=0}$ that converges to $\dot{u}^{k(0)}_{n,T+1} = 1$. **Note that this guess includes the exogenous climate damage and amenity change components**.
- **Step 2**: For all $t \geq 0$, use the guess $\{\dot{u}^{k(0)}_{n,t+1}\}^T_{t=0}$ and the initial migration shares across markets $\pi^{ks}_{ni,-1}$ to solve for the trajectory of migration shares $\{\pi^{ks}_{ni,t}\}^T_{t=0}$ [using equation (44)].
- **Step 3**: Use the trajectory of $\{\pi^{ks}_{ni,t}\}^T_{t=0}$ and the initial labor allocation/supply across sectors $L^k_{n,0}$ to solve for the trajectory of labor allocations/supply $\{L^k_{n,t}\}^T_{t=0}$ [using equation (46)].
- **Step 4**: Use the trajectory of labor allocations in Step 3 to solve the production side for each period (see algorithm for the inner loop above). This yields the trajectories for wages and prices $\{\dot{w}^k_{n,t+1}, \dot{P}^k_{n,t+1}\}^T_{t=0}$. From $\{\dot{w}^k_{n,t+1}, \dot{P}^k_{n,t+1}\}^T_{t=0}$ we have the trajectory of real wages $\{\dot{\omega}^k_{n,t+1}\}^T_{t=0}$.
- **Step 5**: For each time t, use $\dot{u}^{k(0)}_{n,t+2}$ from the initial guess [Step 1], the migration shares $\{\pi^{ks}_{ni,t}\}^T_{t=0}$ from Step 2, the real wages $\dot{\omega}^k_{n,t+1}$ from Step 4, and **the exogenous time changes in amenities** $\dot{B}_{n,t+1}$ to solve for $\dot{u}^{k(1)}_{n,t+1}$ [using equation (45)]. This yields a new path of $\{\dot{u}^{k(1)}_{n,t+1}\}^T_{t=0}$.
- **Step 6**: If $\{\dot{u}^{k(0)}_{n,t+1}\}^T_{t=0} \approx \{\dot{u}^{k(1)}_{n,t+1}\}^T_{t=0}$ i.e. the maximum difference across all t is less than some pre-specified tolerance level, $\{\dot{u}^{k(0)}_{n,t+1}, \pi^{ks}_{ni,t}, L^k_{n,t}\}^T_{t=0}$ is the solution to the problem. Otherwise update the initial guess to be $\{\dot{u}^{k(1)}_{n,t+1}\}^T_{t=0}$ and repeat the steps until convergence.

Combining the algorithms for the inner and outer loops, we can solve for the sequential competitive equilibrium numerically given an initial allocation of the economy and an anticipated convergence sequence of time changes in fundamentals.

F.2 Simulating the Model for 2015–2100

With the numerical algorithm for solving the model in time changes, our next step is to simulate our full model forward to determine the impacts of climate change for 2015–2100.

F.2.1 Climate Projections

To produce our counterfactual outcomes for the future simulations we use temperature projections from the Coupled Model Intercomparison Project (CMIP5), that correspond to specific Shared

Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs). Specifically, we use the RCP 4.5 scenario for warming. This scenario corresponds to RCP4.5 which yields radiative forcing of 4.5 W/m^2 at the end of the century and moderate economic growth. RCP4.5 is often considered an intermediate, high probability scenario. End of century global average warming is approximately 2.5°C along this scenario where CO_2 concentrations reach above 550ppm. We use the associated SSP2 scenario to determine the location-specific paths of exogenous economic growth.

F.2.2 Simulation Steps

Using these temperature projections, we compute the impacts of climate change by simulating our model forward assuming constant fundamentals, except for the impact of temperature on productivity and amenities[30]. In particular, we do so via three steps:

Step 1: Solve the baseline economy with climate change in time changes We capture the initial year 2015 levels from observed actual migration and trade flows, which are sufficient statistics in our model. Simulating forward from 2015, the annual change in fundamental productivity $\dot{Z}_{i,t}^k$ comprises two components:

$$\dot{Z}_{i,t}^k = \frac{Z_{i,t}^k}{Z_{i,t-1}^k} = \left(1 + \wp_{i,t}^k\right) \exp\left[g(\boldsymbol{T}_{i,t}; \zeta_{\mathbf{Z}}) - g(\boldsymbol{T}_{i,t-1}; \zeta_{\mathbf{Z}})\right].$$

The first component is the base growth rate $\left(1 + \wp_{i,t}^k\right)$ which we compute using the country-specific growth rates from the SSP2 socioeconomic scenario which is recommended to be used alongside the RCP 4.5 warming scenario. The trajectories are plotted in the appendix in Figure B.2. The second component is the impact of temperature on productivity levels. The temperature response function for productivity $g(\boldsymbol{T}_{i,t}; \zeta_{\mathbf{Z}})$ is estimated from historical data as outlined in Section 2.2 and the country-specific within-year daily temperature distributions $\boldsymbol{T}_{i,t}$ follow our chosen climate scenario described above. We construct the time change in amenities in a similar fashion:

$$\dot{B}_{n,t} = \dot{\overline{B}}_{n,t} \exp\left[\left(f(\boldsymbol{T}_{i,t}; \zeta_{\mathbf{B}}) - f(\boldsymbol{T}_{i,t-1}; \zeta_{\mathbf{B}})\right)\right].$$

where the temperature response function for amenities $f(\boldsymbol{T}_{i,t}; \zeta_{\mathbf{Z}})$ is estimated from historical data as outlined in Section 2.3, the temperature distributions follow our chosen climate scenario, and we assume that $\dot{\overline{B}}_{n,t} = 1$ so changes in amenities are solely given by the effect of temperature. We assume that the remaining time-varying fundamentals – i.e. trade costs and migration costs – are held constant at their initial year 2015 value and use the numerical algorithm for outlined in

[30]The primary difference between our future simulation and the historical simulation in CDP is that we do not observe actual migration or trade flows through the end of the century and thus cannot fully capture all the time-varying fundamentals in our model. Thus, we simulate the model forward using constant fundamentals.

appendix F.1 to solve the baseline economy[31]. We then extend the simulations to 2200 assuming $\dot{Z}^k_{i,t} = \dot{B}_{i,t} = 1$ after year 2100 to allow the economy to converge to a new steady state.

Step 2: Solve the counterfactual economy without climate change in time changes We solve the counterfactual economy without climate change in time changes, where the distribution of daily temperatures is now held constant at their year 2015 levels while the other time-varying fundamentals remain identical to our setup for the baseline economy. We also extend the simulations to 2200 assuming $\dot{Z}^k_{i,t} = \dot{B}^k_{i,t} = 1$ after year 2100 to allow the economy to converge to a new steady state.

Step 3: Compute counterfactual outcomes To compute the counterfactual outcomes, we then divide the outcomes of our simulated baseline economy in Step 1 against their counterparts in our simulated counterfactual economy without climate change in Step 2. Thus, our results can be interpreted as the effects of climate change, i.e. the effect of changes in temperature given the SSP2 RCP 4.5 scenario, relative to holding all local daily temperature distributions constant at their initial levels.

F.3 Quantitative Decomposition of Economic Channels and Adaptation Mechanisms

The above steps allow us to measure the full impacts of climate change. To further quantify the effect of different economic channels and market-based adaptation, we conduct simulations in which we shut down or fix different parts of the model.

Quantifying the role of different structural economic features in magnifying or dampening the effect of climate change is relatively straightforward because these are changes to exogenous attributes of the model. We are interested in the role of five structural attributes. The first channel is the transmission of climate shocks through within-region input-output loops. We expect that input-output loops may play a significant role in the effect of climate change because it provides a mechanism for climate shocks to a particular market to propagate throughout the economy by altering input prices or demand for intermediates. For example, a negative shock to wood and paper production can propagate downstream and raise input costs for newspaper and books producers, while negative shocks to agriculture may harm food manufacturers.[32] We quantify the impact of these feedbacks by comparing results from an economy with input-output loops to one without

[31]Note that even though productivity is time varying, it is pinned down exogenously so we can simulate the economy using constant fundamentals.

[32]The literature has found that micro shocks propagate through input-output networks and generate substantial aggregate effects (e.g. Acemoglu et al., 2012; Baqaee and Farhi, 2020; Bigio and La'o, 2020; Carvalho et al., 2021) See Carvalho and Tahbaz-Salehi (2019) for a review on production networks and the propagation of shocks.

them. We remove input-output loops by setting the shares of intermediates in production equal to zero: $\gamma_n^{ks} = 0$ for all n, k and s.

We quantify the impact of amenities impacts by comparing results to a model where the amenities response function is fixed to zero. We quantify the impact of forward-looking US households by simulating the model with a discount factor of zero so that households ignore the future, although we use the primary calibrated value to compute welfare. We quantify the impact of industry heterogeneity by simulating our model with the productivity response function in Figure 2 instead of Figure 3. We quantify the impact of representing daily temperature by reducing a year's temperature for each market to be entirely in its annual average 1°C bin. We quantify the impact of the remaining structural attributes channels described below in a similar fashion.

Identifying the role of adaptation through trade, migration across locations, and industry switching is more complex. For example, to understand the value of adaptation through trade we cannot simply solve the model under autarky since autarky is not the right counterfactual comparison. The proper counterfactual is a world where trade still occurs, but does not adjust in response to climatic shocks. Here we describe our approach to decompose the benefits of market-based adaptation. The key step is that in our simulations with climate change, we fix trade and migration shares to their trajectories derived from an identical model that was not affected by climate change. This eliminates adaptation in response to climate change along each channel without completely shutting down movement of goods and labor. We compare the results from these constrained simulations against the results from the simulations described earlier where all the adaptation channels are active. The difference between the two gives us the impacts of adaptation through trade and labor reallocation. In what follows we present the theoretical basis of our approach and detail the adjustments required to our solution algorithms for the full model described above.

F.3.1 Identifying Trade Adaptation

We formally identify the role of trade adaptation with the following proposition.

Proposition 5. *Suppose that the exogenous trajectories of trade shares* $\{\overline{\lambda}_t\}_{t=0}^{\infty}$ *and the time changes in productivities* $\{\dot{Z}_t\}_{t=0}^{\infty}$ *and trade costs* $\{\dot{\tau}_t\}_{t=0}^{\infty}$ *are known. Then given the time-t momentary equilibrium allocation* $\{L_t, X_t\}$*, the solution to the time-t+1 momentary equilibrium* $\{L_{t+1}, X_{t+1}\}$

without trade adjustment *can be obtained from the following system of nonlinear equations:*

$$\dot{x}^k_{n,t+1} = \left(\dot{L}^k_{n,t+1}\right)^{\gamma^k_n \psi_n} \left(\dot{w}^k_{n,t+1}\right)^{\gamma^k_n} \prod_{s=1}^{K} \left(\dot{P}^k_{n,t+1}\right)^{\gamma^{ks}_n}, \tag{47}$$

$$\dot{P}^k_{n,t+1} = \left[\sum_{i=1}^{N} \overline{\lambda}^k_{ni,t} \dot{Z}^k_{i,t+1} \left(\dot{x}^k_{i,t+1} \dot{\tau}^k_{ni,t+1}\right)^{-\theta^k}\right]^{\frac{1}{\theta^k}}, \tag{48}$$

$$X^k_{n,t+1} = \sum_{s=1}^{K} \gamma^{ks}_n \sum_{i=1}^{N} \overline{\lambda}^k_{in,t+1} X^k_{i,t+1} + \alpha^k \left(\sum_{k=1}^{K} \dot{w}^k_{n,t+1} \dot{L}^k_{n,t+1} w^k_{n,t} L^k_{n,t} + \iota_n \chi_{t+1}\right), \tag{49}$$

$$w^k_{n,t+1} L^k_{n,t+1} = \gamma^k_n \left(1 - \psi^k\right) \sum_{i=1}^{N} \overline{\lambda}^k_{in,t+1} X^k_{i,t+1}, \tag{50}$$

where $\chi_{t+1} = \sum_{i=1}^{N} \sum_{s=1}^{K} \frac{\psi_i}{1-\psi_i} w^s_{i,t+1} L^s_{i,t+1}$.

For a given set exogenous trajectories of time changes in fundamentals, Proposition 5 together with Proposition 4 allow us to generate equilibrium trajectories of the economy without trade shares changing endogenously. In our results, we fix the exogenous trajectory of trade shares equal to the equilibrium trade shares from the full unconstrained model (Propositions 1 and 2) without climate change. Comparing the equilibrium outcomes of this trade share-constrained economy shocked by climate change against the outcomes from the full unconstrained model shocked by climate change allows us to determine the role of adjustment through trade. More concretely, our procedure for identifying the role of trade adaptation in the forward simulations is as follows:

- Step 1: Run the full baseline algorithm with climate change to get the full baseline economy with climate change
- Step 2: Run the full baseline algorithm to get the full counterfactual trajectories without climate change
- Step 3: Save the trajectory of trade shares
- Step 4: Run the baseline algorithm but with trade shares fixed to the ones from Step 2 (using Proposition 5) to obtain the baseline economy with climate change but without trade adaptation
- Step 5: Compare the results from Step 1 and 4 to attain the role of trade adaptation

F.3.2 Identifying Adaptation Through Labor Reallocation

Proposition 6. *Suppose that the trajectories of exogenously given labor reallocation shares* $\{\overline{\pi}_t\}_{t=0}^{\infty}$, *time changes in productivities* $\{\dot{Z}_t\}_{t=0}^{\infty}$, *and time changes in trade costs* $\{\dot{\tau}_t\}_{t=0}^{\infty}$ *are known. Then the sequential competitive equilibrium in time changes* ***without labor market adjustment*** *is* *given by the sequence* $\{\dot{\omega}^k_{n,t}\left(\dot{\bar{L}}_t, \dot{Z}_t, \dot{\tau}_t\right)\}_{t=0}^{\infty}$ *that solves equations (39)-(43) at each time* t*, where the exogenous trajectory of* $\dot{\bar{L}}_t$ *is constructed from the trajectory of baseline migration shares given.*

In this proposition, the intertemporal decisions of the household become completely exogenous because migration shares and industry switching are both made exogenous. Our procedure for identifying the role of labor reallocation (both migration across regions and industry switching) is as follows:

- Step 1: Run the full baseline algorithm with climate change to get the full baseline economy with climate change
- Step 2: Run the full baseline algorithm to get the full counterfactual trajectories without climate change
- Step 3: Save the trajectory of migration shares
- Step 4: Run the baseline algorithm but with migration shares fixed to the ones from Step 2 (using the first part of Proposition 6) to obtain the baseline economy with climate change but without migration adaptation
- Step 5: Compare the results from Step 1 and 4 to attain the role of labor reallocation adaptation

G Additional Results

In this appendix we provide additional results and robustness checks for our model-implied temperature response functions, reduced form climate response functions, and quantitative exercises on the impacts of climate change from 2015-2100.

G.1 Estimation Robustness of Response Functions

Tables G.1 and G.2 show the robustness of our coefficient estimates for our productivity and amenities response functions. In both tables, our main specification is in column 4. Columns 1–3 build up the fixed effects to our main specifications. Columns after column 4 vary the fixed parameters: the trade elasticity, migration elasticity, and discount factor. The estimates are highly robust to the choice of fixed effects and controls, although, as expected, the migration elasticity plays a key role in the valuation of amenities.

Table G.3 shows the robustness of our reduced form response function for the effect of a change in climate on expected welfare. Our main specification is Column 2 which exactly matches the model-implied regression. Columns 3–4 increase the granularity of our fixed effects. Columns after column 4 vary the fixed parameters: the trade elasticity, migration elasticity, and discount factor. The estimates are again highly robust, with the results being most sensitive to the assumed migration elasticity.

Figure G.1 plots several different estimates of our response functions. The left panels show the productivity response functions, the middle panels show the amenities response functions, and the right panel show the reduced form response functions for welfare. The top row shows estimates using orthogonal polynomials of degrees 2–4, with our main specification in red. The bottom show estimates using cubic splines with 1–3 evenly spaced knots. In general, all the response functions are similar except the higher order response functions which tend to be steeper at higher temperatures.

Table G.1: The effect of daily temperature on productivity.

	(1)	(2)	(3)	(4)	(5)	(6)
First-Degree Orthog. Poly.	−0.044***	−0.044***	−0.044***	−0.044***	−0.035***	−0.053***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Second-Degree Orthog. Poly.	−0.051***	−0.051***	−0.051***	−0.051***	−0.044***	−0.064***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Third-Degree Orthog. Poly.	−0.021***	−0.021***	−0.021***	−0.021***	−0.018***	−0.028***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Num.Obs.	310571	310571	310571	310571	310571	310571
Input/Trade Cost Controls	Yes	Yes	No	Yes	Yes	Yes
Origin FE	Yes	No	No	No	No	No
Destination FE	Yes	No	No	No	No	No
Industry FE	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	No	No	No	No
Orig x Dest FE	No	Yes	No	No	No	No
Orig x Dest x Industry FE	No	No	Yes	Yes	Yes	Yes
Industry x Year FE	No	No	Yes	Yes	Yes	Yes
Trade Elasticity	Base	Base	NA	Base	All 4	All 8

Robust standard errors are clustered two ways at the origin and destination levels.

* p < 0.1, ** p < 0.05, *** p < 0.01

G-2

Table G.2: The effect of daily temperature on amenities.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First-Degree Orthog. Poly.	−0.117***	−0.037*	−0.003	0.073**	0.078***	0.072**	0.048	0.090***
	(0.021)	(0.021)	(0.013)	(0.029)	(0.030)	(0.029)	(0.030)	(0.028)
Second-Degree Orthog. Poly.	−0.086***	−0.111***	0.004	−0.067***	−0.074***	−0.065***	−0.028**	−0.109***
	(0.014)	(0.019)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
Third-Degree Orthog. Poly.	−0.004	0.005	0.016*	0.058**	0.065**	0.057**	0.035	0.074***
	(0.013)	(0.022)	(0.009)	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)
Num.Obs.	50341	50341	51552	50341	50341	50341	50341	50341
Wage/Future Migration	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	No	No	No	No	No	No	No
Destination FE	Yes	No	No	No	No	No	No	No
Industry FE	Yes	Yes	No	No	No	No	No	No
Year FE	Yes	Yes	No	No	No	No	No	No
Orig x Dest FE	No	Yes	No	No	No	No	No	No
Orig x Dest x Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Discount Factor	.98	.98	.98	.98	.90	.999	.98	.98
Migration Elasticity	2.02	2.02	2.02	2.02	2.02	2.02	1.02	3.02

Robust standard errors are clustered two ways at the origin and destination levels.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

G-3

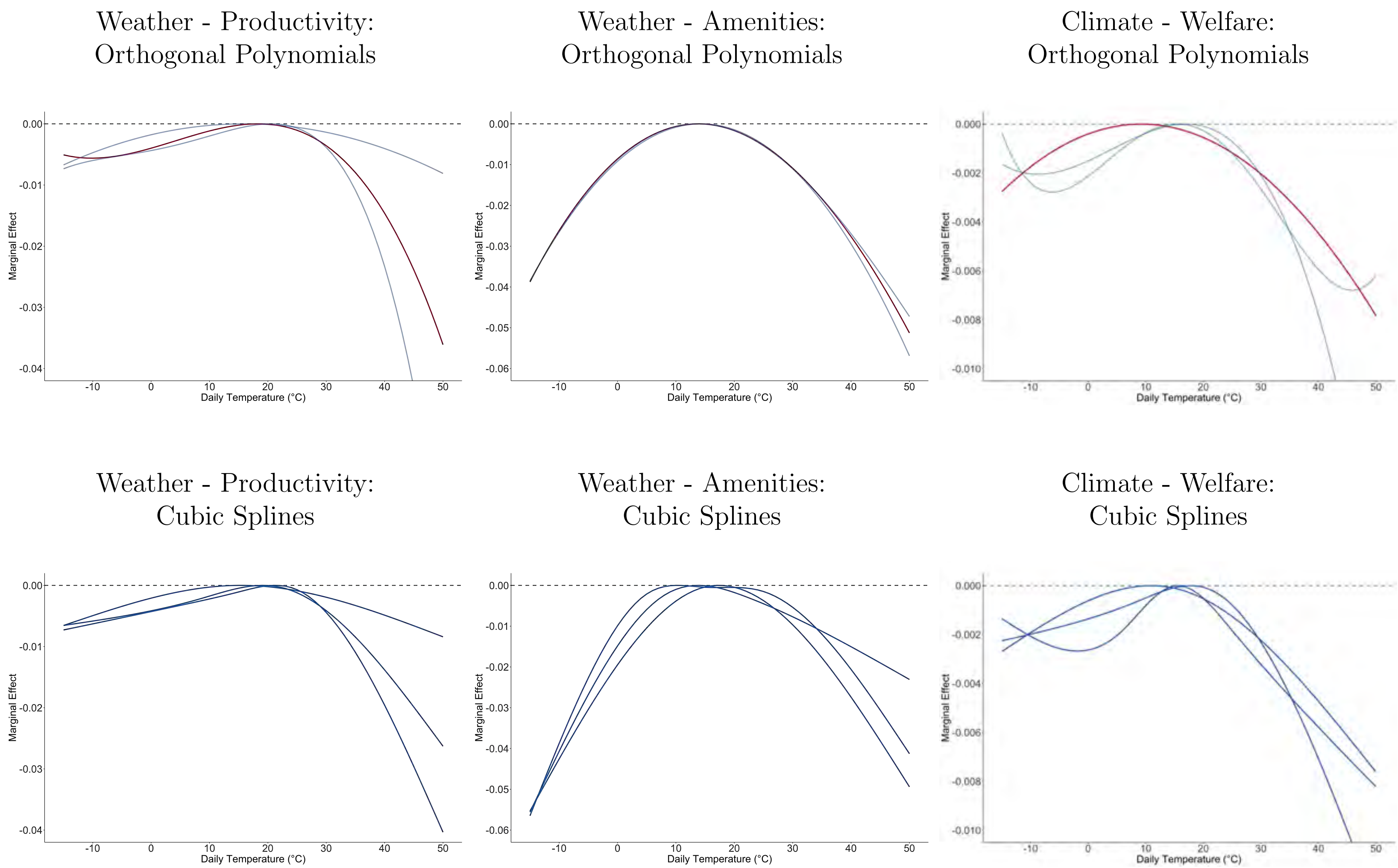
Table G.3: The reduced form effect of climate on welfare.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First-Degree Orthog. Poly.	−0.023**	−0.023**	−0.053***	−0.026***	−0.022**	−0.024**	−0.046***	−0.016
	(0.010)	(0.010)	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Second-Degree Orthog. Poly.	−0.018**	−0.018**	−0.042***	−0.020***	−0.017*	−0.018**	−0.035***	−0.012
	(0.008)	(0.009)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Third-Degree Orthog. Poly.	−0.009**	−0.008**	−0.020***	−0.010***	−0.008*	−0.009**	−0.017***	−0.006
	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Num.Obs.	101893	101893	101893	101893	101893	101893	101893	101893
Destination FE	Yes	No	Yes	No	No	No	No	No
Origin FE	No	No	Yes	No	No	No	No	No
Industry FE	Yes	No	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Industry x Year FE	No	No	No	Yes	No	No	No	No
Dest x Industry FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Orig x Industry FE	No	No	No	Yes	No	No	No	No
Discount Factor	.96	.96	.96	.96	.90	.99	.96	.96
Migration Elasticity	2.02	2.02	2.02	2.02	2.02	2.02	1.02	3.02

Robust standard errors are clustered two ways at the origin and destination levels.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure G.1: Productivity, amenities, and reduced form climate response functions under alternative polynomial and cubic spline approximations.



Note: The top left panel shows the productivity response functions for sets of polynomials from degree 2 to 4. The top middle panel shows the amenity response functions for sets of polynomials from degree 2 to 4. The top right panel shows the reduced form climate response functions for sets of polynomials from degree 2 to 4. The red line is our preferred specifications in the main text. The bottom left panel shows the productivity response functions for 2 to 4 cubic splines (1 to 3 knots). The bottom middle panel shows the amenity response functions for 2 to 4 cubic splines (1 to 3 knots). The bottom right panel shows the reduced form climate response functions for 2 to 4 cubic splines (1 to 3 knots). The peak of the response functions have been normalized to zero for plotting.

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G.2 Additional Results from Quantitative Simulations

An advantage of our quantitative approach is that it allows us to decompose welfare impacts into different channels, as well as derive a range of impacts of climate change beyond welfare. Here we provide additional results such as the direct welfare effect of amenity impacts, the impacts on migration and employment across industries, and a decomposition of trade adaptation.

G.2.1 Additional Results on the Value of Economic Features and Adaptation Mechanisms

Table G.4 shows the same results as Table 1, but where we remove each structural feature from our full structural model. This will generate different welfare changes because the different features have non-additive impacts on welfare. Nonetheless, we see that amenity impacts, sectoral heterogeneity in temperature response functions, and extreme temperature (by incorporating daily temperature) have large implications for welfare, like in Table 1 in the paper.

Table G.5 shows the same results as Table 2 but where we shut down each adaptation channel relative to the full model. Shutting down labor reallocation reduces welfare because trade enhances the benefits of labor mobility.

G.2.2 Direct Welfare Effect of Amenity Impacts

Figure G.2 plots the direct welfare effect of amenities (e.g. $\log \widehat{B}_{i,t}$), ignoring any indirect effects on real wages. Climate impacts on amenities are worst in the South and improve as one goes north. Alaska experiences an improvement in amenities equivalent to a welfare improvement of 50%.

G.2.3 Population and Employment Trends

Figures G.3 and G.4 plot the time series of the change in population and employment shares due to climate change. The figures plot the effects under four scenarios: our full model, the model with a homogeneous response function across sectors, the model where households are myopic, the model where trade does not adjust in response to climate change, and the model where labor does not adjust.

A few common themes can be seen in the graphs. First, having homogeneous damages tends to amplify migration trends. Second, shutting down trade dampens industry switching and migration which is consistent with labor reallocation and trade being complementary. Third, removing forward-looking behavior also significantly dampens industry switching and migration because myopic households cannot adjust in response to expected longer-run climate change.

G.2.4 Trade Adaptation Decomposition

Figure G.5 decomposes the effect of trade on welfare presented in Figure 7. The effect of trade can be decomposed into two pieces in our model. The first is what we call the pure trade competition effect. This effect is from buyers substituting away from sellers in the South, which further reduces welfare in the region on top of wage declines from negative productivity shocks. This is shown in the left panel and is computed the same as the top left panel of Figure 7, but without input-output linkages. The two maps are similar except here the welfare impact is shifted negatively.

The second piece is the input-output amplification of trade competition. The reason the magnitudes are shifted to be more negative is because input-output linkages amplify the aggregate benefits of trade competition: producers make similar trade substitutions as consumers. This always increases welfare from trade competition as shown in the right panel and it accounts for half of the total effect of trade. The welfare values shown in the right panel are the difference between the top left panel of Figure 7 and the left panel of Figure G.5.

Table G.4: US welfare contribution of model attributes relative to the full model.

	United States		Global	
	Without Market Adaptation	With Market Adaptation	Without Market Adaptation	With Market Adaptation
Full Structure Welfare	**-4.1%**	**-3.1%**	**-21.1%**	**-21.7%**
Remove Input-Output Linkages	-0.1pp	-0.7pp	-0.2pp	+0.2pp
Remove Amenities	+3.4pp	+3.1pp	+17.8pp	+17.6pp
Remove Forward-Looking US Households	+0pp	-0.8pp	+0pp	+0pp
Remove Industry Heterogeneity	-2.5pp	-3.3pp	-4pp	-4.3pp
Remove Daily Temperature	-1.5pp	-1.5pp	+1pp	+0.9pp
Remove All	+5.9pp	+5.4pp	+16.2pp	+16.2pp

Note:
Rows 2-7 show the difference in welfare between our full model and a model without the listed attribute for the median GCM. All rows use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all rows holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

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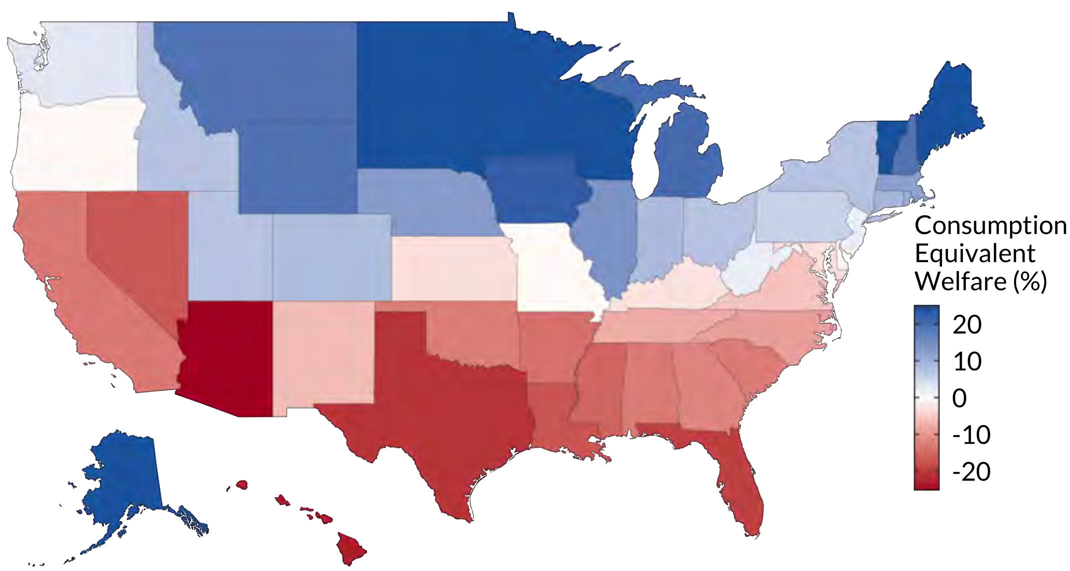
Table G.5: US welfare contribution of adaptation through trade, migration, and industry switching: 2015–2100.

Full Structure + Full Adaptation Welfare	Remove Trade Adjustments	Remove Migration and Industry Switching	Remove All
-3.1%	-1pp	-0.3pp	-1pp

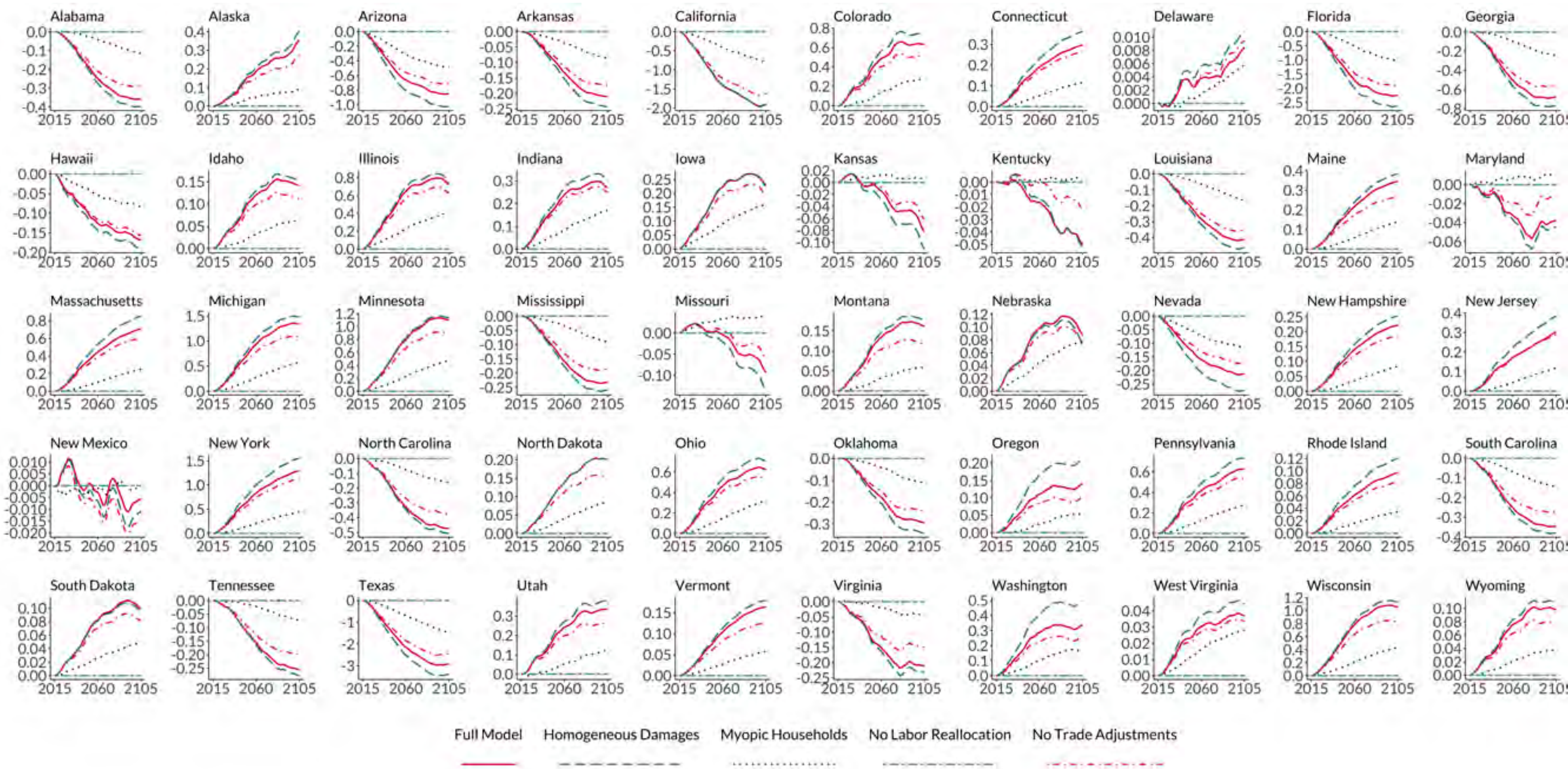
Note:
Each row shows the difference in welfare between our full model with all market-based adaptation, and a model without the listed adaptation mechanism. All rows use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all rows holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

Figure G.2: The direct welfare value of changes in amenities 2015–2100.



Note: The values on the map plot the direct climate impacts on amenities from equation (21). The map shows results from our full model with all structural and adaptation channels. The map uses daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and uses the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for the map holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

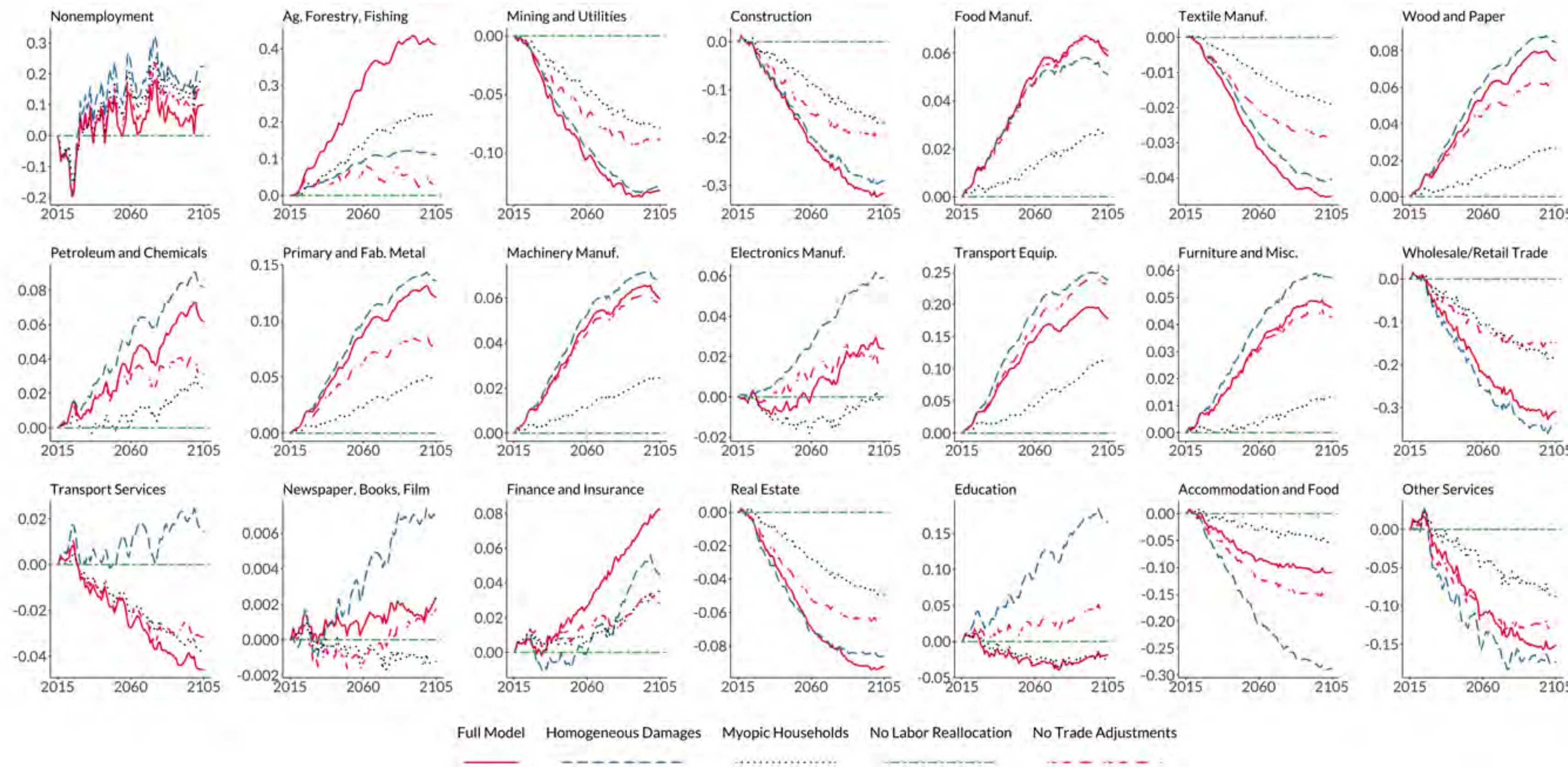
Figure G.3: State population trends.



Note:

The units are the percentage point changes in population relative to no climate change counterfactual. The units are the fraction of total US population so total population sums to 1 and the total change sums to zero. All panels show results from our full model with all structural and adaptation channels except for the adjustment noted in the legend. All panels use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all panels holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

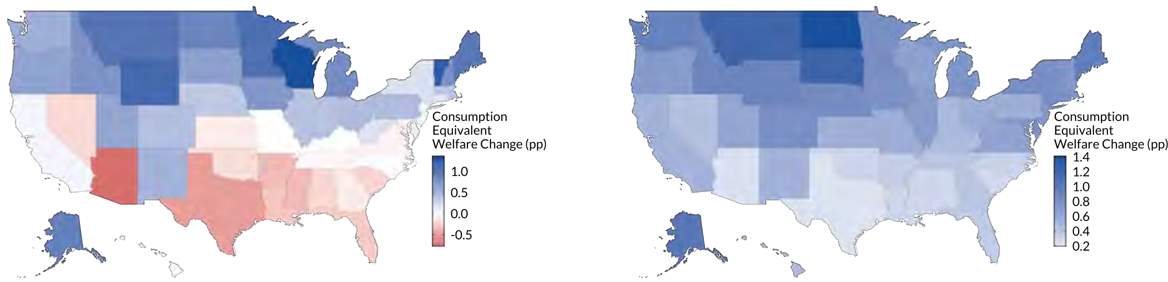
Figure G.4: Industry employment trends.



Note: The units are the percentage point changes in employment relative to no climate change counterfactual. The units are the fraction of total US population so total population sums to 1 and the total change sums to zero. All panels show results from our full model with all structural and adaptation channels except for the adjustment noted in the legend. All panels use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all panels holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.

Figure G.5: Decomposing the welfare value of trade: 2015–2100.

Trade Competition | IO-Amplification of Trade Competition



Note: The left panel is the pure trade competition effect: the adaptation benefits of trade without input-output linkages. The right panel is how input-output linkages amplify the trade competition effect: the difference between the top left panel of Figure 7 and the left panel here. All panels use daily temperatures averaged across 17 RCP 4.5 GCMs as the climate change shock and use the SSP2 growth rates for baseline productivity growth. The counterfactual scenario for all panels holds the annual temperature distribution for each location constant at its 2015 level. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals to allow the full impacts of the shocks to unfold.