The Economic Effects of Climate Change in Dynamic Spatial Equilibrium

Ivan Rudik, Gary Lyn, Weiliang Tan, and Ariel Ortiz-Bobea*

November 17, 2021

Abstract

We present two approaches for analyzing the economic effects of climate change with a focus on the United States: a new dynamic envelope theorem method for welfare effects, and a quantitative dynamic-spatial equilibrium model for comprehensive impacts. We find that climate change reduces welfare globally, but increases welfare in the US. Adaptation through trade and labor reallocation provides moderate net benefits, but with substantial heterogeneity across states. Migration tends to benefit states in the South and harm states in the North, trade has the opposite effect, and reallocation of labor across industries benefits almost all states. Adaptation through labor reallocation and trade are complementary and significantly boost welfare more together than the sum of their individual benefits. We show that structural features of the economic and climate, such as input-output linkages and daily temperature, are essential for properly measuring welfare. We compare welfare estimates from the envelope theorem and quantitative results and find them to be highly consistent, indicating our quantitative model captures the first-order economic factors for climate change. 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.

JEL: F18, O13, Q54

Keywords: climate change, global warming, adaptation, geography, trade, general equilibrium, social cost of carbon

*Rudik: Charles H. Dyson School of Applied Economics and Management, Cornell University. Lyn: Department of Economics, Iowa State University. Tan: Charles H. Dyson School of Applied Economics and Management, Cornell University. Ortiz-Bobea: Charles H. Dyson School of Applied Economics and Management, Cornell University. We thank Ed Balistreri, Farid Farrokhi, Karen Fisher-Vanden, Russell Hillberry, Sam Kortum, Joel Landry, Ashley Langer, Derek Lemoine, Shanjun Li, Joe Shapiro, Chong Xiang, Yoto Yotov, and seminar participants at Arizona, Gothenburg, Penn State, Purdue, the Philadelphia Fed, UMass, the AEA Annual Meeting, the Columbia-Cornell-MIT Environmental Workshop, the Empirical Trade Online Seminar, the Ron Jones Workshop, the Virtual Seminar on Climate Economics, the Virtual International Trade and Macro Seminar, and the Young Scholars Symposium on Natural Resources for helpful comments. Diego Cardoso provided excellent research assistance.

Climate change will significantly alter our planet and the global economy. Increased prevalence of extreme heat is already affecting exposed industries, reducing aggregate productivity growth heterogeneously across sectors and space (Burke et al., 2015; Diffenbaugh and Burke, 2019; Ortiz-Bobea et al., 2021; Politico, 2021; Nath, 2020; Miller et al., 2021), and propagating through supply chains (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 (Missirian and Schlenker, 2017; The New York Times, 2020), 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 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 in 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 key intuition behind deploying the envelope theorem in a dynamic setting is that in-migration flows, conditional on a location fixed effect and common time effect, 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 change in i's climate. Our set up requires minimal assumptions and allows us to remain agnostic about whether there are growth versus level effects on productivity, the households' preferences for temperature, and whether households and firms adapt via capital investments like air conditioning in addition to purely market-based mechanisms like migration or job switching. Our estimates show that the climate response function is inverse-U-shaped in daily temperature such that extreme cold and extreme hot days both reduce welfare compared to more moderate days.

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. In our second approach, we develop a dynamic spatial multi-industry general equilibrium model to go beyond solely welfare results. In our model, changes in the within-year distribution of daily average temperature affect productivity growth heterogeneously across 20 different industries (Dell et al., 2012; Burke et al., 2015; Colacito et al., 2018), and also directly impact the utility of households through local amenities.[1,2]

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.[3] Production and the flow of goods can also reallocate across space in response to climate-driven changes in productivity. We leverage this additional structure to quantify impacts on welfare, migration, and employment; and to decompose the role of market-based adaptation and the structure of the economy in welfare outcomes. 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 the quantitative model are appropriate.

In order to link the quantitative economic model to the climate, we develop new estimation strategies that use the model's macro-structure to estimate the productivity growth and utility effects of transient temperature — or any general weather variable — accounting for dynamic and spatial interactions. To simulate the impacts of climate change in the quantitative model, we require an estimate of the effect of weather on model variables, rather than the effect of a change in climate. 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. The simulation results then reflect the actual welfare impacts of climate change given the model's assumptions.

Our approach for estimating the effect of temperature on industry-specific productivity growth exploits variation in bilateral trade flows across countries relative to own expenditures.[4] 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 the aggregate productivity growth has a robust, non-linear relationship with daily temperature indicating that extreme hot and extreme cold days reduce growth relative to moderate days. Replacing a single day of the year at the optimal productivity growth temperature of 16°C with an extreme hot day at 32°C reduces growth by 0.3 percentage points. We also estimate industry-specific response functions and find substantial heterogeneity in

[1] Effects on growth have been used in DICE-based integrated assessment models (Dietz and Stern, 2015; Moore and Diaz, 2015). One technical reason empirical researchers have focused on growth effects instead of level effects is because of unit roots in aggregate production and the associated difficulties with inference (Burke et al., 2015).

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

[3] 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.

[4] 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 identification. Section D.3 in the appendix demonstrates how standard approaches motivated by production function estimation are confounded by spatial linkages.

climate impacts across 20 different industries both in terms of optimal temperature and sensitivity to extremes. Optimal temperatures mostly fall into the range of 14°C–20°C. Industries that are more exposed to the elements such as mining, wood and paper production, and construction tend to be more sensitive to temperature extremes. The industries least sensitive to extreme heat are services like accommodations, real estate, and education.

The second channel for temperature impacts is through local amenities. We estimate the effect of temperature on local amenities and flow utility with a fixed effects transformation 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 decreasing and concave in daily temperature such that replacing a single day at the optimal amenity temperature of 14°C with a hot day at 30°C results in a decline in welfare of 0.2%.

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 of daily temperature is held constant at its 2005–2014 average.[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, forward-looking households, 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 the reduced form model.

In our basic model — which omits market adaptation and structural features like input-output linkages — climate change results in welfare gains in colder parts of Europe and North America, but significant losses elsewhere. The median global impact is a welfare loss of 12.9%, while the US has median welfare gains of 0.1%. In our full model, which includes all the structural features, the welfare magnitudes are amplified: US welfare improves by 4% while global welfare declines by 17%. We decompose the welfare impact of different structural features and find that industrial heterogeneity, daily temperature extremes, input-output linkages, and forward-looking behavior are all important for measuring welfare.

Allowing for market-based adaptation in the full model leads to even larger welfare gains in the United States. The US gains from adaptation because households migrate north where tem-

[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 and to be able to report the uncertainty in our results from differences across GCMs (Auffhammer et al., 2013).

peratures are better for amenities and productivity, and workers can move out of heat-sensitive industries into those that are less harmed by hotter temperatures. 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. Trade, industry switching, and migration by themselves each boost aggregate US welfare by 2 to 4 percentage points, but with large spatial heterogeneity. Trade actually worsens welfare in the South through intensifying export competition, and migration worsens welfare in the North through pecuniary externalities on local real wages. Trade adaptation alone is highly regressive and migration alone is highly progressive. When combined, the three adaptation mechanisms increase US welfare by 15 percentage points — more than the sum of their parts because of complementarities between trade and labor reallocation — and the distributional effect is progressive.[6] Combining all three mechanisms generates welfare gains for virtually the entire US except for states like Alaska and North Dakota where accelerated in-migration drives down real wages for incumbent households. The large aggregate gains from market-based adaptation in the US rely on three necessary components: trade, migration or industry switching, and forward-looking household behavior. If any of the three are missing then the gains from market-based adaptation are significantly attenuated.

We test the assumptions of our quantitative model by shocking it and the reduced form model with the same climate change scenario. If the quantitative model perfectly matched reality, and the limited assumptions in the reduced form model were correct, the average welfare level and the distribution of relative welfare differences across regions in both approaches should be similar. We find that the distribution of relative welfare differences across regions are extremely close across the two approaches.[7] The level of the quantitative welfare estimates are consistently positively biased by several percentage points relative to the reduced form estimates, suggesting that the quantitative model may be missing a factor common across many regions — such as sea level rise, uncertainty about future climate states, or mis-estimated trade elasticities. The fact that the quantitative model is capturing the margins of heterogeneity and geography that are important for climate change gives us confidence in the results it generates, with the caveat that the level of welfare may be biased upward.

We contribute to a nascent literature at the intersection of climate impacts, growth, 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

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

[7]The slope of a regression of the welfare results from one model on the other is approximately 1 with a Pearson correlation of 0.4.

et al., 2020; Cruz and Rossi-Hansberg, 2021; Cruz, 2021; Desmet et al., 2021). Efforts similar to ours in the macroeconomics literature have aimed to bridge the gap between micro-estimates and macro-modeling of the growth effects of natural disasters (Bakkensen and Barrage, 2021).

We advance this literature in several ways. First, we consider a highly granular set of 20 industries. Second, our dynamic spatial framework allows us to quantify the value of several adaptation mechanisms and the structure of the model. Third, our paper provides evidence that extreme temperature and industrial heterogeneity matter for welfare. Four, 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.[8] The estimation approach only requires data on a small set of variables and does not require calibrating or inverting the full general equilibrium model, thereby reducing the influence of particular calibration choices. Estimating a single equilibrium condition is a simple procedure and thus usable by researchers interested in applying these techniques solely for impact estimation and not simulating the full model.[9]

We also contribute to the empirical climate literature by providing two new empirical frameworks. A significant share of the current literature aims to understand under what conditions simple fixed effects regressions of outcomes on weather and other variables identifies the marginal effect of a change in climate — the unobserved population distribution of weather — on firm or consumer welfare (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Deryugina and Hsiang, 2017; Mérel and Gammans, 2018; Lemoine, 2021).[10] 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 first framework, we show how to recover the present value of a household's stream of discounted expected utility under several common assumptions in the trade and industrial organization literatures. We can then take advantage of the envelope theorem by regressing it on temperature, a location-industry effect, and a year effect to identify the effect of a change in climate.

In our second framework, we provide a way to recover well-identified estimates of the marginal impact of a change in the distribution of local weather on *productivity growth* and *flow utility*, two non-optimized variables of interest to economists. One attractive feature of our approach is that

[8]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.

[9]Although our paper includes substantial detail on reallocation and impacts on growth 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).

[10]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.

our specifications clearly show how and why dynamics and spatial linkages matter for identifying how changes in the distribution of weather affect productivity and utility. Ignoring spatial linkages biases impacts of extreme weather toward zero and ignoring dynamic behavior biases the optimal amenity temperature downward.

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

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

We start by introducing a formal dynamic spatial model of household location and industry choice. 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 static literature employing this 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 solving for the expected value.[11] One of the innovations in our paper is showing how to recover the representative household's expected value function while imposing relatively few assumptions on the overall economy.

1.1 A Parsimonious Dynamic Model of Household Location and Industry Choice

Our model builds on the dynamic discrete choice framework of Artuc et al. (2010). There are N regions and K industries in the economy. In the initial time period $t = 0$ 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 $\beta \in (0, 1)$. At every time period t — here, a year — households in each region either supply their one unit of labor inelastically to a specific industry, or are non-employed and engage in home production ($k = 0$). Households in each region-industry pair, which we call a *market*, obtain a flow utility $U^k_{n,t}$ at time t which may be a function of consumption, local weather, adaptation measures, and profits from the firms that they own in the region. Households then observe the conditions of the economy and climate in all labor markets, and the realization of an additive idiosyncratic utility shock $\epsilon^s_{i,t}$ that we assume is distributed Type-I Extreme Value for tractability. At the end of each time period, households choose whether to relocate to another

[11] 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.

market (i,s), with migration costs μ_{ni}^{ks} that are time-invariant, specific to each origin-destination pair of markets, and measured in terms of utility. The optimization problem for a household in market (n,k) at time t is:

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

where ν is a scalar that captures the migration elasticity of households across markets, $v_{n,t}^{k}$ is the time t welfare for a household in market (n,k), $\mathbb{E}_{\epsilon}$ indicates the expectation over future idiosyncratic shocks, and $\mathbb{E}_t$ indicates expectations over other uncertain state variables. Households will choose to move to the market (i,s) with the highest present value stream of future expected utility minus any migration costs. Letting $V_{n,t}^{k} \equiv \mathbb{E}_{\epsilon}\left[v_{n,t}^{k} \right]$ and taking an expectation with respect to ϵ over equation (1) yields:

$$V_{n,t}^{k} = U\left(C_{n,t}^{k}, B_{n,t} \right) + \nu \log \left(\sum_{i=1}^{N} \sum_{s=0}^{K} \exp \left[\left(\beta \mathbb{E}_t \left(V_{i,t+1}^{s} \right) - \mu_{ni}^{ks} \right) / \nu \right] \right). \tag{2}$$

As is common in the industrial organization literature, the Type-I Extreme Value assumption on the idiosyncratic shocks delivers a convenient closed form expression for migration shares. Defining $\pi_{ni,t}^{ks}$ as the share of households that move from market (n,k) to market (i,s) at time t, we obtain:

$$\pi_{ni,t}^{ks} = \frac{\exp\left[\left(\beta \mathbb{E}_t \left(V_{i,t+1}^{s} \right) - \mu_{ni}^{ks} \right) / \nu \right]}{\sum_{l=1}^{N} \sum_{h=0}^{K} \exp\left[\left(\beta \mathbb{E}_t \left(V_{l,t+1}^{h} \right) - \mu_{nl}^{kh} \right) / \nu \right]}. \tag{3}$$

Equation (3) shows that, all else constant, there will be greater in-migration to markets with higher lifetime net utilities.

1.2 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 discrete nature of the problem means that individual households are not choosing actions which set the gradient of welfare to be zero, but choosing amongst a finite set of actions that maximizes their welfare but does not guarantee a zero gradient. 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 continuous envelope theorem may not apply and weather variation may not identify the effect of a change in climate.

To circumvent this issue, we take advantage of the fact that there is a mass of households in each location and that there exists a representative household (Anderson et al., 1988). The representative household in each market (n,k) makes continuous choices of the levels of a set of migration probabilities from (n,k) to all markets, $\pi_{ni,t}^{ks} \in [0,1]$. Formally,

Proposition 1. *A representative household problem consistent with the individual household's discrete choice problem with aggregate migration shares* (3) *is given by:*[12]

$$v_{n,t}^{k} = \max_{\{\pi_{ni,t}^{ks}\}_{i=1,s=0}^{N,K}} U_{n,t}^{k} + \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks}\left[\mathbb{E}_t\left(V_{i,t+1}^{s}\right) - \mu_{ni}^{ks}\right] - \nu \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks}\log \pi_{ni,t}^{ks} \tag{4}$$

$$s.t \quad \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks} = 1, \qquad 0 \leq \pi_{ni,t}^{ks} \leq 1 \quad \forall\, n,i,k,s,t.$$

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. This effect captures the dispersion in payoffs that arises from the idiosyncratic shocks which then generates dispersion in location choices by individual households. 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 $\mathbb{E}_t\left(V_{i,t+1}^{s}\right)$. 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 no difference in the potential payoffs of the individual households in (n,k), and so they will all migrate to the same market (i,s) where $\mathbb{E}_t\left(V_{i,t+1}^{s}\right) - \mu_{ni}^{ks}$ is the highest. This is equivalent to representative household in (n,k) putting probability 1 on the location with the highest value.

1.3 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 $\mathbf{C_t}$ as the *global* climate at time t, captured by a vector of relevant parameters — for example, expected global average surface temperature — that characterizes the distribution of *realized* global variables such as actual global average temperature. $\mathbf{C_{n,t}}$ is the *local* climate in region n at time t which is a function of the global climate and location-specific variables such as elevation, latitude, and longitude. We remain agnostic about the exact relationship between the global and local climates. $\mathbf{T_{n,t}}$ represents the *realized* distribution of weather variables in region n at time t. These are drawn from 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 realized distribution of weather captured by $\mathbf{T_{n,t}}$, what we actually observe in the data, will not equal the population distribution $\mathbf{C_{n,t}}$ which is our object of interest.

[12] It is straightforward to show that solving the representative household's constrained maximization problem yields the aggregate migration shares from the individual household problems in a competitive equilibrium, given by equation (3).

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 equality constraint on the sum of migration shares, and let $\bar{\rho}_{ni}^{ks}$ and $\underline{\rho}_{ni}^{ks}$ be the multipliers associated with the upper and lower bounds on individual migration shares. Omitting arguments for clarity, $\mathcal{L}_{n,t}^{k}$ is the Lagrangian associated with (1):

$$
\begin{aligned}
\mathcal{L}_{n,t}^{k}(\cdot) \coloneqq{} & \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks}\left[\mathbb{E}_t\left(V_{i,t+1}^{s}\right) - \mu_{ni}^{ks}\right] - \nu \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks} \log \pi_{ni,t}^{ks} \\
& + \rho\left[1 - \sum_{i=1}^{N}\sum_{s=0}^{K} \pi_{ni,t}^{ks}\right] + \sum_{i=1}^{N}\sum_{s=0}^{K}\left[\underline{\rho}_{ni}^{ks}\pi_{ni,t}^{ks} + \bar{\rho}_{ni}^{ks}\left(1 - \pi_{ni,t}^{ks}\right)\right].
\end{aligned}
\tag{5}
$$

Differentiating equation (5) with respect to the local climate and applying the constrained optimization envelope theorem gives us the following:

$$
\begin{aligned}
\frac{\partial v_{n,t}^{k}}{\partial C_{n,t}} &= \underbrace{\frac{\partial \mathcal{L}_{n,t}^{k}}{\partial \pi_{ni,t}^{ks}}}_{=0} \frac{\partial \pi_{ni,t}^{ks}}{\partial \mathbf{T_{n,t}}} \frac{\partial \mathbf{T_{n,t}}}{\partial \mathbf{C_{n,t}}} + \frac{\partial \mathcal{L}_{n,t}^{k}}{\partial \mathbb{E}_t\left(V_{i,t+1}^{s}\right)} \frac{\partial \mathbb{E}_t\left(V_{i,t+1}^{s}\right)}{\partial \mathbf{T_{n,t}}} \frac{\partial \mathbf{T_{n,t}}}{\partial \mathbf{C_{n,t}}} \\
&= \frac{\partial \mathcal{L}_{n,t}^{k}}{\partial \mathbb{E}_t\left(V_{i,t+1}^{s}\right)} \frac{\partial \mathbb{E}_t\left(V_{i,t+1}^{s}\right)}{\partial \mathbf{T_{n,t}}} \frac{\partial \mathbf{T_{n,t}}}{\partial \mathbf{C_{n,t}}} \\
&= \beta \mathbb{E}_t\left(\mathbb{E}_\epsilon\left[\sum_{i=1}^{N}\sum_{s=1}^{K} \pi_{ni,t}^{ks} \frac{\partial \mathbb{E}_t\left(V_{i,t+1}^{s}\right)}{\partial \mathbf{T_{i,t}}} \underbrace{\frac{\partial \mathbf{T_{i,t}}}{\partial \mathbf{C_{i,t}}}}_{=1}\right]\right) \\
&= \beta \mathbb{E}_t\left(\mathbb{E}_\epsilon\left[\sum_{i=1}^{N}\sum_{s=1}^{K} \pi_{ni,t}^{ks} \frac{\partial \mathbb{E}_t\left(V_{i,t+1}^{s}\right)}{\partial \mathbf{T_{i,t}}}\right]\right)
\end{aligned}
$$

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 effect of a change in some climate variable is thus just the direct effect of the observed weather variable on future value. Intuitively, at an optimum, 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). 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.

1.4 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 entire economy. To satisfy these conditions we make two additional assumptions:

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

Assumption 2. *Migration costs are separable in origin and destination components, i.e.* $\mu_{ni}^{ks} = \mu_n^k + \mu_i^s$.

Assumption 1 ensures that the household value function captures the full welfare of the economy, while Assumption 2 implies that migration costs take on a particular structure and has been used in similar settings (Desmet and Rossi-Hansberg, 2015; Conte et al., 2020; Cruz and Rossi-Hansberg, 2021).

Under Assumption 2, equation (3) can be written as:

$$\pi_{ni,t}^{ks} = \frac{\exp\left[\left(\beta\mathbb{E}_t\left(V_{i,t+1}^s\right) - \mu_n^k - \mu_i^s\right)/\nu\right]}{\sum_{l=1}^N \sum_{h=0}^K \exp\left[\left(\beta\mathbb{E}_t\left(V_{l,t+1}^h\right) - \mu_n^k - \mu_l^h\right)/\nu\right]}.$$

We can then cancel the origin migration cost terms μ_n^k in the exponentials. The denominator is then identical across all markets at time t and we relabel it $\exp(\tilde{\delta}_t) \equiv \sum_{l=1}^N \sum_{h=0}^K \exp\left[\left(\beta\mathbb{E}_t\left(V_{l,t+1}^h\right) - \mu_l^h\right)/\nu\right]$. Finally, solve for the expected value term in the numerator:

$$\mathbb{E}_t[V_{i,t+1}^s] = \frac{\nu}{\beta}\log\pi_{ni,t}^{ks} + \frac{1}{\beta}\mu_i^s + \frac{\nu}{\beta}\tilde{\delta}_t.$$

We can express a market's expected value as the sum of log in-migration flows, a time-invariant component specific to the market, and a component common across all markets at each time t. 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 structural 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 then write down the following regression of migration shares on temperature variables and fixed effects:

$$\log\pi_{ni,t}^{ks} = \frac{\beta}{\nu}h(\mathbf{T_{i,t+1}}; \zeta_\mathbf{D}) + \delta_t + \varphi_i^s + \varepsilon_{ni,t}^{ks} \tag{6}$$

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 local change in climate and below we will describe how we construct h as a function of daily temperature data. 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 make clear what features of the climate-economy this approach fully captures. First, no where in the model have we assumed exactly 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, or any other channel. Second, we have 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 accounting for expectations about future climate. These features allow us to stay agnostic about exactly how climate change and adaptation affects the economy, and the structure of production and utility while still recovering the effects of a change in climate.

We note two limitations of the reduced form approach in this paper. The first is that we only have bilateral migration shares within the US and thus can only compute US welfare. The second is that any change in a climate variable common to all locations — such as global average temperature — will be collinear with $\tilde{\delta}_t$, so we cannot use an envelope theorem approach to understand the effect of a change in global climate statistics. Instead, we must focus on local climate and use weather variables that are varying within a location and over time such as regional temperature.[13]

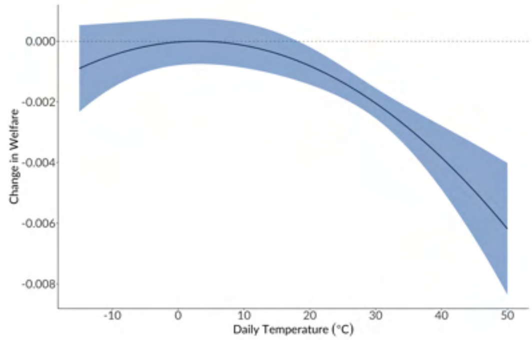
1.5 Constructing the Temperature Response Functions

Our model and estimation approach applies to any aspect of climate change such as temperature, precipitation, humidity, and sea levels. In our estimation and quantitative results we focus on the temperature component of the climate, specifically the distribution of daily average temperature within each year t. We construct our temperature response function by starting with the distribution of daily average 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 that region n's daily average temperature lies in that bin. The values across all 1°C bins then sum up to the number of days in a year. The total annual effect on our outcomes of interest is the sum of the individual daily effects across the bins. We Windsorize the distribution so there is a lower bin containing all daily temperatures $\leq$-15°C and an upper bin containing daily temperatures $\geq$50°C. Similar to Schlenker and Roberts (2009), we evaluate each daily temperature bin using a second-degree orthogonal polynomial, and sum up the first and second-degree terms across all days of the year.[14] $h(\mathbf{T_{i,t}};\zeta_\mathbf{C})$ thus captures the effect of observed daily temperature in region i on migration shares into region i, and hence welfare in region i. The level of h at each temperature tells us the effect of an additional day of the year at that temperature on welfare. The data required for estimating our temperature response functions are presented in appendix C.1.

[13] Previous work has implicitly done this as well by including unit and time fixed effects (Deschênes and Greenstone, 2007; Deryugina and Hsiang, 2017). One potential way to circumvent collinearity of global weather variables is to construct unit-time specific measures of weather across other locations. One example would be a distance weighted average of temperature across the global reflecting the fact that weather in closer locations may matter more because of trade and migration frictions.

[14] An alternative way to describe this is we are using a second-degree approximation to force a particular relationship between our temperature bins rather than estimating 66 separate coefficients.

Figure 1: The reduced form welfare-climate response function (left) and the welfare effect of a change in local climate (right).



Left: The response function is constructed using a second degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are Windsorized at -15°C and 50°C. The shaded area denotes the 95% confidence intervals. The response function is estimated using equation (6). Standard errors are clustered at the state level.

1.6 Reduced Form Results

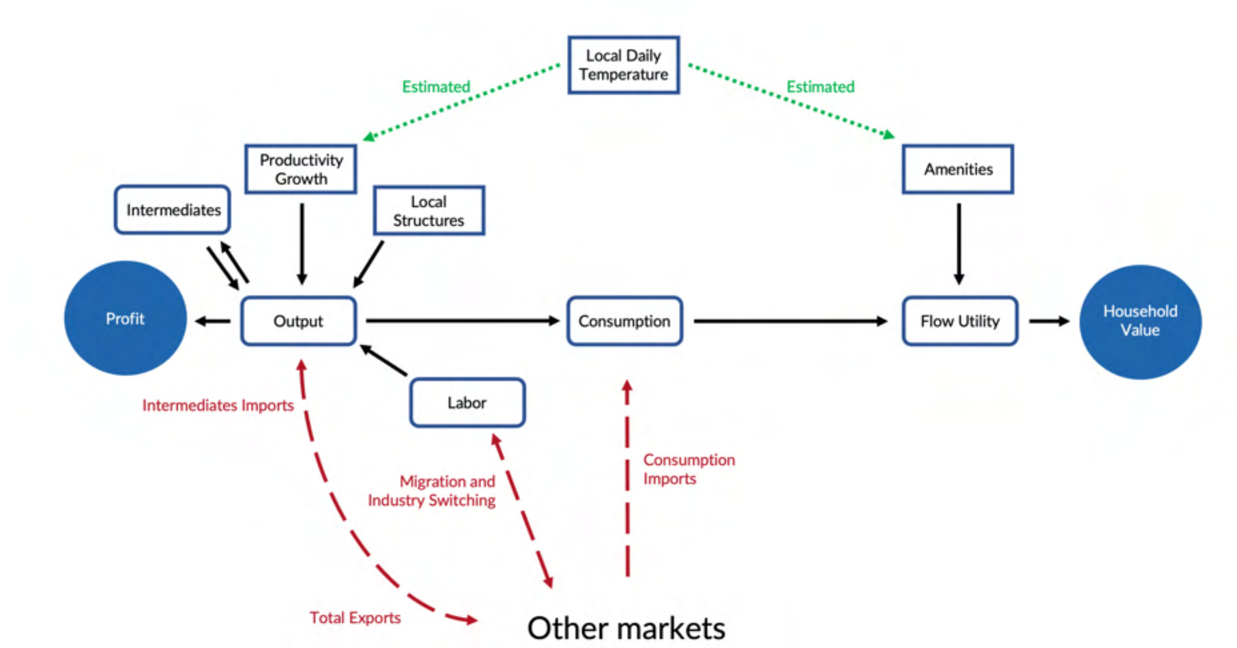
Figure 1 plots our reduced form results using the envelope theorem approach. The left panel plots the reduced form response function for a change in climate estimated from equation (6). The response function is inverse-U shaped and peaks at a daily temperature of 3°C, but we cannot reject a peak as high as 10°C at a 95% confidence level. The estimates indicate that if a region has a single hot day at 32°C instead of at the optimal temperature of 3°C welfare in that year declines by 0.2%. An extreme cold day at -15°C only reduces welfare by 0.1%. Appendix F shows that this response function is robust to alternative estimation approaches. At the end of the quantitative results we revisit the reduced form response function to test the quantitative model assumptions.

2 A Dynamic Spatial Quantitative Model with Climate Change

We now impose more structure to examine welfare, the role of different economic features, and the value of market adaptation. 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 productivity growth and local 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 2 depicts the structure of the model for a single market (region-industry). In every 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 temperature in a location affects the growth of firm productivity.

Figure 2: 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.

Time is discrete and denoted by t. In our model each time period t represents one year. 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. 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 migration decisions 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.

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

$$B_{n,t} = \bar{B}_{n,t}\exp\left(f(\mathbf{T_{n,t}}; \zeta_{\mathbf{B}})\right) \tag{7}$$

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 choose to consume goods from each industry s, $c_{n,t}^{ks}$, which aggregates to an overall basket of goods from different industries given by:

$$C_{n,t}^k = \prod_{s=1}^{K}\left(c_{n,t}^{ks}\right)^{\alpha^s}, \tag{8}$$

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 $c_{n,t}^{ks}$ 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:

$$P_{n,t} = \prod_{s=1}^{K}\left(P_{n,t}^s/\alpha^s\right)^{\alpha^k} \tag{9}$$

where $P_{n,t}^s$ 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, which are similar to the ones in Section 1. In the initial time period there is a mass of $L_{n,0}^k$ 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 $\epsilon_{i,t}^{s}$. At the end of each time period, households choose whether to relocate to another market (i, s) in the same country, with migration costs μ_{ni}^{ks} that are time-invariant, specific to each origin-destination pair of markets, and measured in terms of utility.[15]

Households will choose to move to the market with the highest present value stream of utility minus any migration costs. The optimization problem for a household in market (n, k) at time t is:

$$v_{n,t}^{k} = \max_{\{i,s\}_{i=1,s=0}^{N,K}} U\left(C_{n,t}^{k}, B_{n,t}\right) + \left\{\beta \mathbb{E}_t \left(\mathbb{E}_\epsilon \left[v_{i,t+1}^{s}\right]\right) - \mu_{ni}^{ks} + \nu \epsilon_{i,t}^{s}\right\} \tag{10}$$

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

where $\mathbb{E}_t(\cdot)$ is the time-t expectation over future state variables which could capture technology shocks, policy shocks which could affect output, climate shocks, and the like. $\mathbb{E}_\epsilon(\cdot)$ is the expectation over the household's future realizations of the idiosyncratic shock.

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. This assumption allows us to aggregate the decision-making of individual households in closed form. Although the model framework admits stochasticity in states and rational expectations, we assume that households in the quantitative model have perfect foresight following CDP due to the binding computational constraint of solving the model under uncertainty.

Given the migration shares in equation (3), 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:

$$L_{n,t+1}^{k} = \sum_{i=0}^{N} \sum_{s=0}^{K} \pi_{in,t}^{sk} L_{i,t}^{s}. \tag{11}$$

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.

[15] For the purposes of our empirical and quantitative application, we only observe migration flows in the US and thus cannot identify μ_{ni}^{ks} in other countries. As a result we assume that there is no migration across countries. We further assume that $\mu_{ni}^{ks} = 0$ 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.

2.2 Production And Labor Demand

Producers in region n and industry k at time t adopt a two-tier Cobb-Douglas constant returns to scale technology:

$$q_{n,t}^{k} = z_{n,t}^{k} \left[(H_n^k)^{\psi^k} (L_{n,t}^k)^{1-\psi^k} \right]^{\gamma_n^k} \prod_{s=1}^{K} \left(M_{n,t}^{ks} \right)^{\gamma_n^{ks}}, \tag{12}$$

where H_n^k are local structures, $L_{n,t}^k$ are labor inputs, and $M_{n,t}^{ks}$ are intermediate inputs produced in industry s in the same region. ψ^k represents the share of local structures in value added, γ_n^k represents the share of value added, and γ_n^{ks} represents 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:

$$x_{n,t}^{k} = \kappa_n^k \left[\left(r_{n,t}^k \right)^{\psi^k} \left(w_{n,t}^k \right)^{1-\psi^k} \right]^{\gamma_n^k} \prod_{s=1}^{K} \left(P_{n,t}^{s} \right)^{\gamma_n^{ks}}, \tag{13}$$

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.[16]

A producer of variety ξ in market (n,k) produces $q_{n,t}^k(\xi)$ units of output, given exogenous productivity $z_n^k(\xi)$. 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:

$$F_{n,t}^{k}(z) = \exp\left[-Z_{n,t}^{k} (z)^{-\theta^k} \right]. \tag{14}$$

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 the fundamental productivity of region n in industry k grows at some time-varying base rate $\wp_{n,t}^k$ but adjusted for temperature effects:

$$\frac{Z_{n,t}^{k}}{Z_{n,t-1}^{k}} = (1 + \wp_{n,t}^{k}) \exp\left(g(\mathbf{T}_{n,t}; \zeta_{\mathbf{Z}}^{k}) \right). \tag{15}$$

$\mathbf{T}_{n,t}$ 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 $\zeta_{\mathbf{B}}$ is a set of parameters to be estimated that govern how weather affects local productivity growth.

2.3 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 $\tau_{nn,t}^k = 1$

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

for all n and k, and $\tau^k_{ni,t} \leq \tau^k_{nl,t}\tau^k_{li,t}$ for all i, n, l and k (triangular inequality). The price of each industry k variety ξ and region n is the minimum unit cost across regions:

$$p^k_{n,t}(\xi) = \min_{1 \leq i \leq N} \left\{ \frac{\tau^k_{ni,t} x^k_{i,t}}{z^k_{i,t}(\xi)} \right\}.$$

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

$$\lambda^k_{ni,t} = \frac{Z^k_{i,t}\left(x^k_{i,t}\tau^k_{ni,t}\right)^{-\theta^k}}{\sum_l Z^k_{l,t}\left(x^k_{l,t}\tau^k_{nl,t}\right)^{-\theta^k}}. \tag{16}$$

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

$$P^k_{n,t} = \Gamma^k \left(\sum_{l=1}^N Z^k_{l,t}\left(x^k_{l,t}\tau^k_{nl,t}\right)^{-\theta^k} \right)^{-1/\theta^k}, \tag{17}$$

where Γ^k is a constant, and $1+\theta^k > \sigma^k$.[17] The latter is the usual technical assumption guaranteeing a well-defined price index.

Finally, our model also allows for trade imbalances. In each location n, there is a mass 1 of immobile local capitalists that own the immobile local structure. The capitalists rent the local structures to producers at rate $r^k_{n,t}$, 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 (8)). Time-varying trade imbalances are thus given by the difference between the time-varying rents capitalists collect, and the income they receive from investing in the global portfolio, i.e. $\sum_{k=1}^K r^k_{n,t}H^k_n - \iota_n\chi_t$, where $\chi_t = \sum_{i=1}^N \sum_{k=1}^K r^k_{n,t}H^k_n$ 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:

$$X^k_{n,t} = \sum_{s=1}^K \gamma^{ks}_n \sum_{i=1}^N \lambda^k_{ni,t}X^k_{i,t} + \alpha^k \sum_{k=1}^K w^k_{n,t}L^k_{n,t} + \alpha^k\iota_n\chi_t. \tag{18}$$

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

[17] 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.

income equals the labor share of expenditures on (n, k) output:

$$w_{n,t}^k L_{n,t}^k = \gamma_n^k (1 - \psi^k) \sum_{i=1}^{N} \lambda_{in,t}^k X_{i,t}^k, \tag{19}$$

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

$$r_{n,t}^k H_n^k = \gamma_n^k \psi^k \sum_{i=1}^{N} \lambda_{in,t}^k X_{i,t}^k. \tag{20}$$

2.4 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 (13) and (16) – (20) 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 (2) – (11) 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.

3 From Theory to Data: Linking Micro-Econometrics and Macro Simulation

Here we describe how we go from the theoretical model to the quantitative results. First, we show how we use the dynamic spatial equilibrium conditions of our model to estimate the effects of weather on productivity growth 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 behavior that are represented by the model. Second, we define the metric we use to compute welfare impacts of climate change. Third, we describe how we simulate the model and decompose the impacts of climate change.

3.1 Trade Flows Identify Effects on Productivity Growth

To estimate the direct effect of temperature on productivity growth, we use the equilibrium conditions of the model governing bilateral trade flows. Appendix Section D.1 shows that we can use equations (16) and (17) to obtain a new equilibrium condition:

$$\log\left(\frac{X^k_{ni,t}/X^k_{nn,t}}{X^k_{ni,t-1}/X^k_{nn,t-1}}\right) = \left[g(\mathbf{T}_{i,t};\zeta^k_{\mathbf{Z}}) - g(\mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}})\right] + \log\left(\frac{1+\wp^k_{i,t}}{1+\wp^k_{n,t}}\right)$$
$$- \theta^k \log\left(\frac{\tau^k_{ni,t}}{\tau^k_{ni,t-1}}\right) - \theta^k \log\left(\frac{x^k_{i,t}}{x^k_{i,t-1}} \Big/ \frac{x^k_{n,t}}{x^k_{n,t-1}}\right).$$

In equilibrium, the change in 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 terms on the first line which correspond to the difference in productivity growth rates between i and n. This component itself is determined by the base growth rate difference, and differences in temperature's effect on growth. If i grows faster than n then n will tend to import more from i relative to purchasing its own productions. The second component is changes in iceberg trade costs over time. 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 growing, then growth in imports from i relative to own expenditures will decline. The last component is the relative input costs. If input costs in i are growing faster than in n, the price of goods from i will be growing faster as well. This decreases growth in 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.

The unit of observation for this equation is an importer-exporter-industry-year. We use the following as our main specification for estimating the response function:

$$\log\left(\frac{X^k_{ni,t}/X^k_{nn,t}}{X^k_{ni,t-1}/X^k_{nn,t-1}}\right) = g(\mathbf{T}_{i,t} - \mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}}) + \theta^k \log\left(\frac{\tau^k_{ni,t}}{\tau^k_{ni,t-1}}\right) + \zeta_{\mathbf{X}}\mathbf{X_t} + \rho^k_t + \varphi^k_{ni} + \varepsilon^k_{ni,t}. \quad (21)$$

We calibrate θ^k to the values estimated in Caliendo and Parro (2015) in order to focus on the estimation of ζ_T. We proxy for time-varying trade costs $\log\left(\frac{\tau^k_{ni,t}}{\tau^k_{ni,t-1}}\right)$ using data on tariffs, and we proxy for input costs by controlling for wages and rental rates of the importer and exporter in $\mathbf{X_t}$. Since g is linear in parameters we have that $g(\mathbf{T}_{i,t};\zeta^k_{\mathbf{Z}}) - g(\mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}}) = g(\mathbf{T}_{i,t} - \mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}})$ and $\zeta^{\mathbf{k}}_{\mathbf{Z}}$ is the vector of coefficients we will estimate. We estimate $\zeta^k_{\mathbf{Z}}$ using Poisson Pseudo Maximum Likelihood (PPML) following the empirical trade literature.[18]

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 the unobserved fundamental growth rates that may be correlated with temperature, time-invariant trade costs, and common shocks to trade costs.

[18] 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.

The error term $\varepsilon^k_{ni,t}$ thus captures within-industry components of fundamental base productivity growth that are changing differentially within an importer-exporter-industry triplet over time. The vector of ζ^k_Z's is well-identified if these components are not correlated with temperature. 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 industry-specific response functions, $\zeta^k_{\mathbf{Z}}$. The industry-specific response functions come from a single regression where we interact the response function g with a set of industry dummy variables.

3.2 Migration Shares Identify Effects on Local Amenities

To estimate the effect of temperature on amenities, we exploit variation in migration flows, wages, and distributions of daily temperature along with equation (2). Section D.2 in the appendix 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 temperature and economic observables:

$$\begin{aligned}\log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) &= \frac{\beta}{\nu}\left[f(\mathbf{T_{i,t+1}};\zeta_{\mathbf{B}}) - f(\mathbf{T_{n,t+1}};\zeta_{\mathbf{B}})\right] + \frac{\beta}{\nu}\log\left(\frac{\bar{B}_{i,t+1}}{\bar{B}_{n,t+1}}\right) \\ &\quad + \frac{\beta}{\nu}\log\left(\frac{\omega^s_{i,t+1}}{\omega^k_{n,t+1}}\right) + \frac{\beta-1}{\nu}\mu^{ks}_{ni} + \beta\log\left(\frac{\pi^{ks}_{ni,t+1}}{\pi^{ss}_{ii,t+1}}\right) + \varepsilon^{ks}_{ni,t}.\end{aligned} \tag{22}$$

Equation (22) must hold in a 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.[19] In equilibrium, this ratio is equal to the sum of four components.

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 $f(\mathbf{T_{i,t+1}};\zeta_{\mathbf{B}}) - f(\mathbf{T_{n,t+1}};\zeta_{\mathbf{B}})$, and differences in unobserved non-temperature related amenities $\frac{\overline{B}_{i,t+1}}{\overline{B}_{n,t+1}}$.

The second component is the one period ahead difference in wages which captures the remaining relative differences in flow payoffs next period. Households will tend to move to the markets with higher real wages, 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.

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

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

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 growth regression, we calibrate β to an annual rate of 0.96 and $\nu = 2.02$ following CDP and Artuc et al. (2010) in order to focus on the estimation of ζ_B. After pinning down β and ν, our specification for estimating the effect of temperature on amenities is:

$$\begin{aligned}\log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) =& \frac{\beta}{\nu}\left[f(\mathbf{T_{i,t+1}} - \mathbf{T_{n,t+1}}; \zeta_{\mathbf{B}})\right] \\ &+ \frac{\beta}{\nu}\log\left(\frac{\omega^{s}_{i,t+1}}{\omega^{k}_{n,t+1}}\right) + \beta\log\left(\frac{\pi^{ks}_{ni,t+1}}{\pi^{ss}_{ii,t+1}}\right) + \delta^k_t + \varphi^k_{ni} + \varepsilon^{ks}_{ni,t} \qquad (23)\end{aligned}$$

where we set $s = k$ since $\zeta_{\mathbf{B}}$ is only identified off migration variation.[20] φ^k_{ni} is an origin-destination-industry effect and δ^k_t is an industry-year effect. These fixed effects are included to full capture the unobserved real world migration costs μ^{ks}_{ni}, and components of local amenities $\frac{\bar{B}_{i,t+1}}{\bar{B}_{n,t+1}}$. $f(\mathbf{T_{i,t+1}}; \zeta_{\mathbf{B}})$ is generated in the same way as $g(\mathbf{T_{i,t+1}}; \zeta_{\mathbf{Z}})$ was for productivity effects using the binned daily temperatures and second-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 as bilateral cross-country migration data is not widely available. Section F in the appendix contains robustness checks for the growth and amenities response function, changing the set of fixed effects, parameter values, and the order of polynomials or splines. Section D.4 in the appendix shows how the response functions vary by a location's average annual temperature over the full sample, which captures how firms and amenities may be adapted to different climates.

3.3 Welfare Definition and Decomposition

We now define our measure of welfare and provide a heuristic analytical decomposition to highlight the role of different adaptation mechanisms in determining 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

[20] 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 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.

δ_n^k 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: $\hat{x}_{t+1} = \frac{\dot{x}_{t+1}}{\dot{x}_t}$. We call the hat variables relative time differences. The consumption-equivalent change in welfare can then be computed using relative time difference variables:

$$\begin{aligned} \log\left(\delta_n^k\right) &= \sum_{t=1}^{\infty} \beta^l \log\left(\widehat{B_{n,t}} \frac{\widehat{C_{n,t}^k}}{\left(\widehat{\pi_{nn,t}^{kk}}\right)^{\nu}}\right) \\ &= \sum_{t=1}^{\infty} \beta^t \left[\underbrace{\log \widehat{B_{n,t}}}_{\substack{\text{direct climate} \\ \text{impact on} \\ \text{amenities}}} \underbrace{- \nu \log \widehat{\pi_{nn,t}^{kk}}}_{\substack{\text{changes in} \\ \text{option value}}} + \underbrace{\log \widehat{w_{n,t}^k} - \log \widehat{P_{n,t}}}_{\text{changes in real wages}} \right]. \end{aligned} \tag{24}$$

The first two terms capture climate impacts on utility, while the last term captures climate impacts on production.

3.4 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 forward from 2015–2100 using projected annual distributions of daily temperature from 17 global climate models under the Representative Concentration Pathways (RCP) 4.5 scenario which 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 the distribution of daily temperature is held to its average level over 2005–2014. The GCMs we use are listed in Section B of the appendix.

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 within-region input-output loops, local amenities, forward-looking household behavior, industrial heterogeneity in temperature response, and the representation of daily temperature versus only using annual means. To identify the role of adaptation through trade, migration across locations, and industry switching, we run simulations with climate change holding the trajectory of trade shares, migration shares, or industry switching shares fixed to their trajectories from the no climate change simulation. See appendix E for more details and C for the data required for the simulations.

4 Quantitative Results

We now present our results. We begin with the estimated model-consistent temperature response functions that pin down the effects of weather in dynamic spatial equilibrium. We then present our results that leverage the full structure of our quantitative model: welfare, the role of different economic channels, and the value of market based adaptation. Finally we show results from our model validation exercise, where the similarity of estimates from both approaches provides further support that our model captures the important features of our economy when computing the welfare impacts of climate change.

4.1 Quantitative Model-Consistent Temperature Response Functions

The left side of Figure 3 shows the average productivity growth response function across all industries from equation (21). In the aggregate, productivity growth has an inverted-U shaped relationship with daily temperature. It peaks at 16°C, consistent with existing evidence that warming tends to increase productivity in cooler climates and reduce productivity in warmer climates (Carleton and Hsiang, 2016).[21] If a single day of the year at 16°C is replaced by a day 32°C, productivity growth declines by 0.3 percentage points.

The average productivity growth response function in Figure 3 masks significant cross-industry heterogeneity. Figure 4 presents the response functions for all 20 industries, where the industries are listed in appendix A. Mining, construction, and agriculture are plotted as the dashed lines and all are relatively sensitive to extreme heat. The manufacturing industries in the solid lines also tend to be heat-sensitive. The service industries are typically the least sensitive to extreme heat. Figure 4 shows there is significant heterogeneity across industries. The peaks of the response functions mostly span from 14°C to 20°C, and some manufacturing industries are up to three-times more sensitive to extreme heat than other service industries.

The right side of Figure 3 shows the amenity response function estimated from equation (23). The amenity response function is inverse-U-shaped and peaks at 14°C, below the productivity response function but above the reduced form welfare response function. Replacing one day at 14°C with one at 30°C reduces welfare by 0.2%.

To get a sense of the size of our results, we compare our estimates to the existing literature estimating effects of daily temperature on output or amenities, or of temperature at higher levels of aggregation on growth. 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,

[21] Figure A3 in the appendix shows that the shape of the growth and amenities response functions is generally robust to choices of higher order polynomials, or using cubic splines.

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 which is in line with our quantitative results later in the paper. Overall, we find that the shape of our response function is similar to previous work that allows for non-linear effects. However, we do generally find larger impacts of extreme hot and cold temperatures on productivity growth compared to the prior literature, which is consistent with our model correctly addressing spatial effects. In Section D.3 in the appendix, we provide intuition and empirically show how the effects of temperature on growth 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 by not account for households' forward-looking actions, estimates amenity effects will be biased as well.

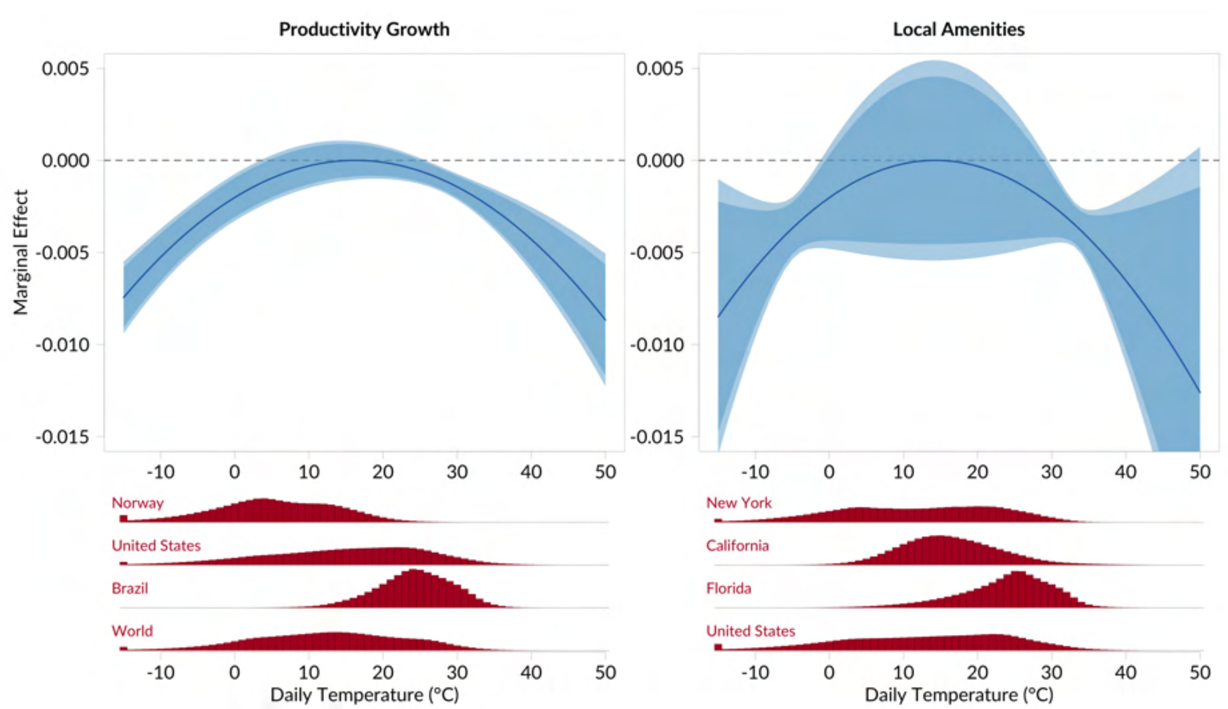
4.2 Impacts of Climate Change in the Basic Model

We now turn to the projected future effects of climate change under RCP 4.5 from 2015–2100 versus a counterfactual world where daily temperature distributions are held constant at their 2005–2014 average. Figure 5 shows the change in the distribution of daily temperature for each state from 2015–2100, averaged across all 17 GCMs. 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 growth 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.

Our first set of welfare results are in Figure 6 which depicts US welfare impacts of future climate change in what we call our *basic model*. This is a stripped down version of the full model presented in Section 2 with no amenities, a common response function across all industries, no input-output loops, myopic households, temperature captured as annual means instead of a set of daily means, and no adaptation through trade or the labor reallocation. 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 generates similar results to aggregate production function approaches that estimate the effect of temperature on GDP growth and then simulate forward in time without accounting for general equilibrium and non-market impacts.

The left panel of Figure 6 plots the welfare change for incumbent households in each state. In the basic model, climate change will have heterogeneous effects across the United States, but

Figure 3: The effect of daily temperature on productivity growth and amenities.



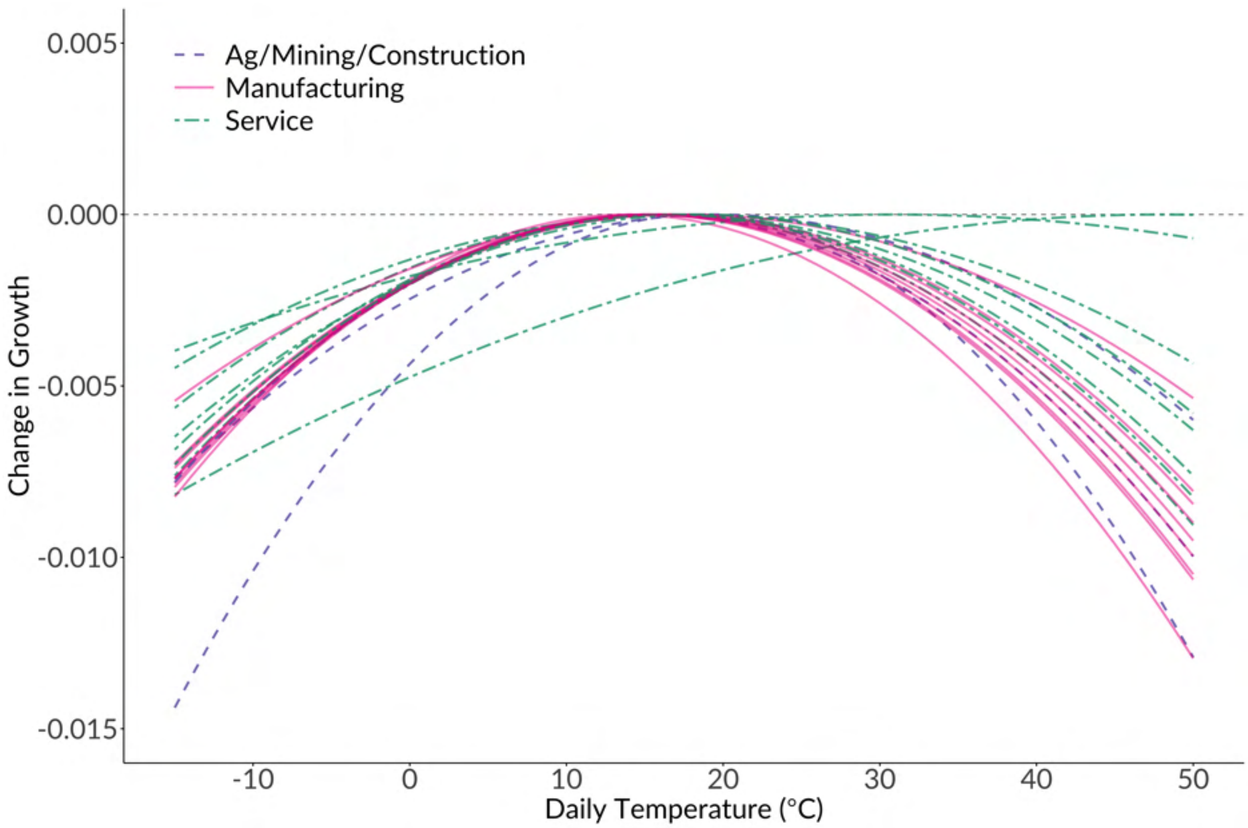
The response functions are constructed using a second degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are Windsorized at -15°C and 50°C. The shaded areas denote the 90% and 95% confidence intervals.

Left: The response function is from estimating equation (21) and reflects the average effect across all industries. Standard errors are clustered two ways at the exporter country and importer country. Figure 4 shows effects separately by industry.

Right: The response function is from estimating equation (23). Standard errors are clustered two ways at the origin state and destination state.

Bottom: The histograms show the distribution of daily average temperature for a set of locations from 2000–2014.

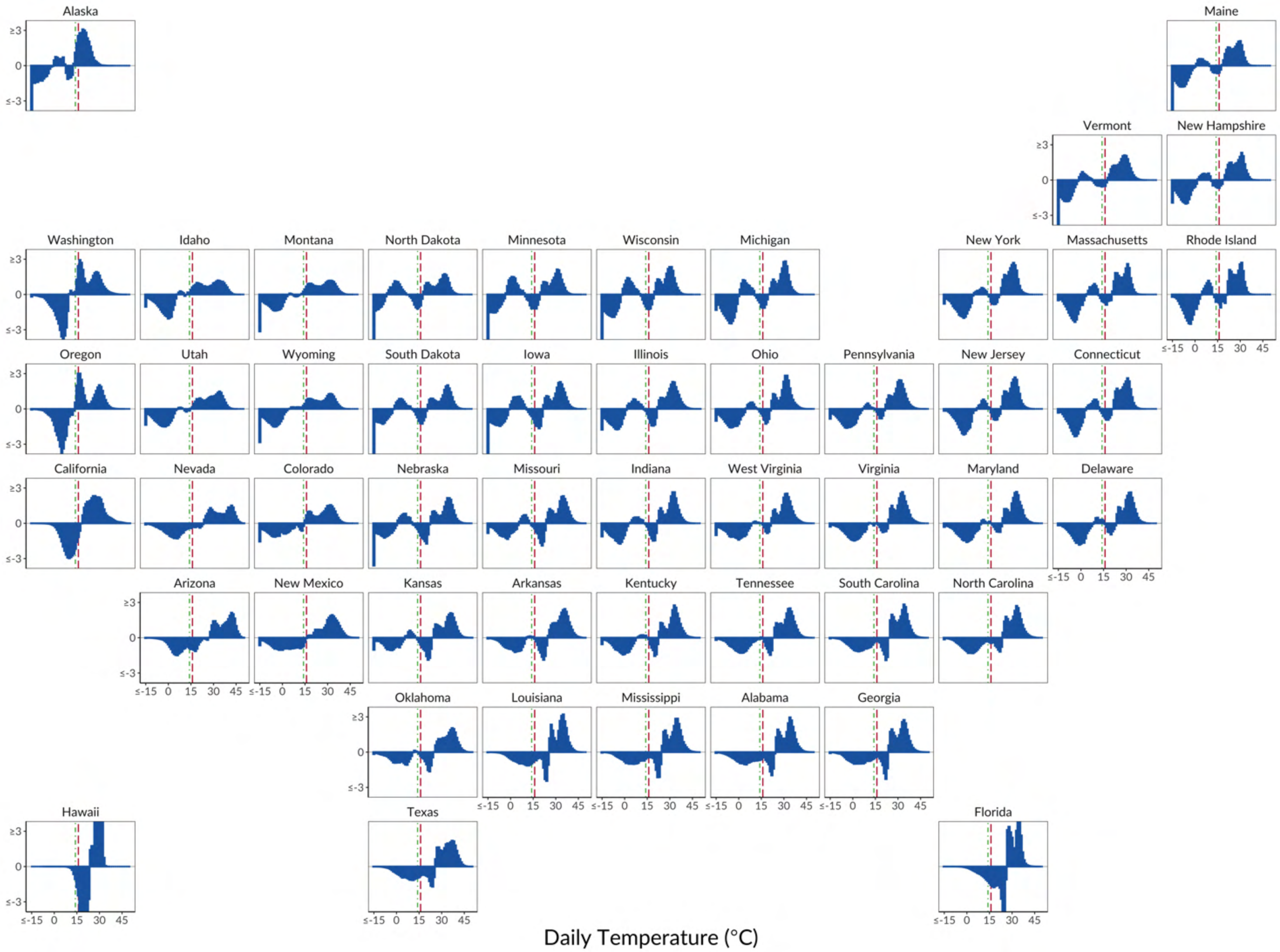
Figure 4: The direct effect of temperature on productivity by industry.



Note: The response functions are constructed using a second degree orthogonal polynomial approximation to the distribution of intra-annual daily temperatures. The shaded areas denote the 95% confidence intervals. The response functions are from estimating equation (21) but where g is interacted with a set of industry dummy variables.

27

Figure 5: Change in within-year daily temperature distributions: 2015–2100.



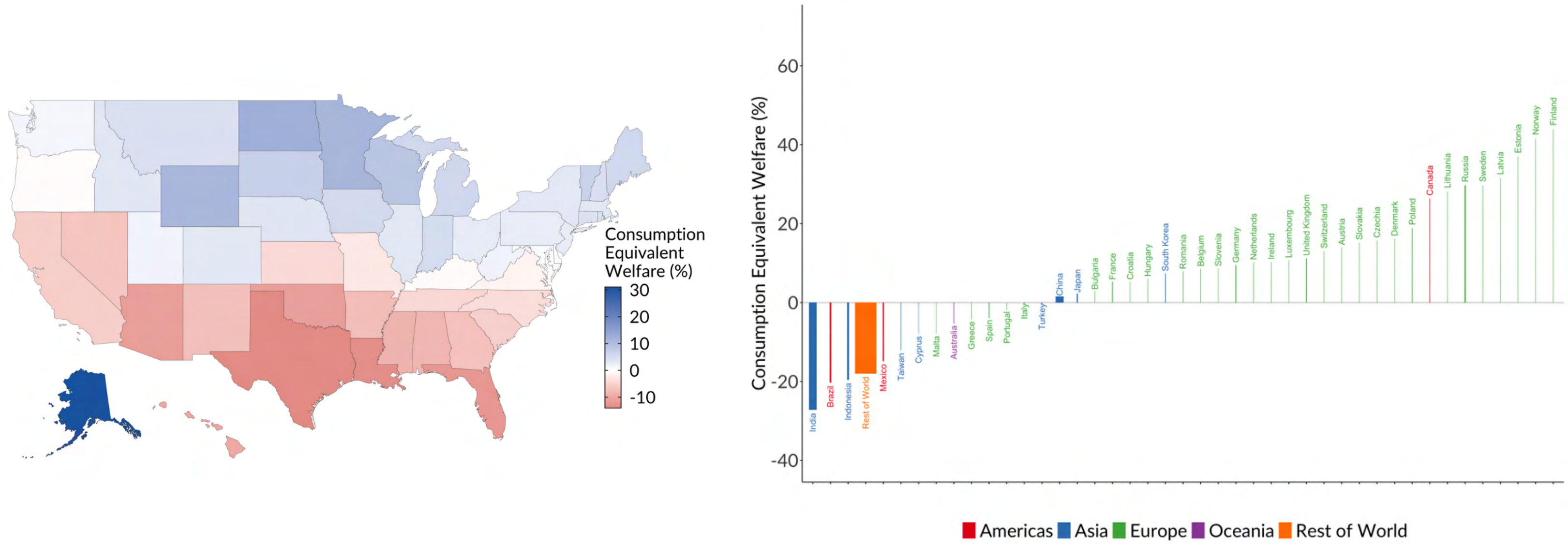
Note: Each plot shows the state-specific change in the number of days in each 1°C temperature bin from the first to last year of the RCP 4.5 climate scenario, averaged over 17 GCMs. Positive numbers denote increases in days at that temperature, negative numbers denote decreases. The temperature distributions are Windsorized at -15°C and 50°C. The vertical red dashed line corresponds to the optimal daily temperature for aggregate productivity growth, and the vertical dash-dotted line corresponds to the optimal daily temperature for local amenities.

approximately a zero aggregate welfare effect. Alaska and states in the Midwest and Northeast are better off, while the South, California, and Nevada suffer losses. In some states like Texas, welfare losses are predicted to be extremely large: nearly 10% in consumption terms. In population average terms, this model predicts the US will gain 0.1%.

The right panel shows welfare results for all other countries. There is significant heterogeneity across latitudes. 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 -12.9%. After accounting for differences in climate change scenarios, our model generates similar results to the previous literature making aggregate estimates of welfare impacts (Burke et al., 2015).[22]

[22] We also find similar distributional results as other quantitative approaches (Cruz and Rossi-Hansberg, 2021), however the levels differ because of differences in modeling of climate impacts.

Figure 6: US and global welfare effects in the basic model without market-based adaptation: 2015–2100.



29

Note: The left panel shows the welfare impact of climate change as a percent of consumption 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 right panel shows welfare results for each country where the width of the bar corresponds to the share of the global population. The counterfactual scenario is if the annual temperature distribution for each location was held constant at its 2000 level for 2015–2100. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals ($\dot{Z}^k_{i,t} = 1$ for all i, k) to allow the full impacts of the shocks to unfold. Both panels show results for the median welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

4.3 The Role of Different Economic Channels

With results from this benchmark model in hand, we now build up to what we call our *full model*, which does not necessarily include adjustments to climate change through trade, migration, or industry switching, but does include amenities, heterogeneous industry responses to temperature, input-output loops, forward-looking households, daily temperature. We first compute the welfare impact of different model attributes by simulating the basic model plus one – or all – of these attributes, and then comparing welfare to the basic model US welfare impacts of 0.1% and global welfare impact of -12.9%.

Recall that δ_n^k denotes our consumption-equivalent change in welfare for market (n, k) from equation (24). Let δ be the population-weighted average of all δ_n^k's in the US in our basic model results shown in Figure 6 and δ^{+H} denote the welfare effect of climate change from a model with attribute H added. Our measure of change in welfare from properly accounting for 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. The remaining rows in Table 1 report Δ^H for a different attribute H. The second and third 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. Temperature effects tend to be amplified through input-output linkages: welfare gains in the US are 1.2pp–3.7pp higher, depending on whether there is market adaptation, while the world is worse off by 3.7pp–7.4pp. 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 worsen welfare, however the aggregate welfare effect is dominated by impacts on productivity growth.

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. The second column shows that, as expected, dynamics have no impact on welfare if households cannot take advantage of being forward-looking by changing their migration and job switching decisions. The third column shows that if households are able to move, then dynamics increase welfare by nearly 3pp in the US. 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 industry-specific temperature response functions with the average response function plotted in Figure 3. Industrial heterogeneity improves US welfare by about 4pp, and global welfare by over 5pp.

The sixth row shows the effect of using daily temperature — which better captures extremely hot and cold days — instead of using annual average temperature. Properly accounting for daily temperature tends to always worsen welfare, especially in the US. The non-linear, concave temperature response functions mean that aggregating away daily effects into annual averages will artificially reduce damages via a Jensen's inequality argument.

The final row shows the effect of adding all attributes to the basic model together. Accounting for these novel features of the climate-economy has heterogeneous effects. Welfare improves in the US, especially with market adaptation, but welfare worsens globally. Additionally, notice that the sum of the welfare effects of adding each attribute individually does not match the welfare effect of adding them all together, indicating that there are non-linear interactions between them. These interactions account for over three-quarters of the US welfare gain without market adaptation (+0.7pp vs +4pp), and nearly two-thirds of the US welfare gain with market adaptation (+5.6pp vs +15.1pp). This discrepancy is smaller for the global welfare outcomes, (-5.8pp vs 4.4pp and -1.7pp vs -0.9pp), but the non-linear interactions tend to worsen global welfare. The difference in magnitude between the US and global interaction effects suggests that forward-looking behavior is a key factor.

These results show that proper representation of the properties of the climate-economy matter, and that the interactions between them have potentially 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. Section F in the appendix presents the same results but where we remove each attribute from the full model instead of adding it to the basic model.

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	**0.1% (1.9%)**	**3% (1.9%)**	**-12.9% (4.7%)**	**-12.7% (4%)**
Add Input-Output Linkages	+1.2pp (2.5pp)	+3.7pp (4.6pp)	-7.4pp (2.1pp)	-3.7pp (2.6pp)
Add Amenities	-0.4pp (0.5pp)	-0.3pp (0.5pp)	-2.6pp (1.3pp)	-2.7pp (1.3pp)
Add Forward-Looking US Households	+0.1pp (0pp)	+2.9pp (1.8pp)	+0pp (0pp)	+0.1pp (0.1pp)
Add Industry Heterogeneity	+4.2pp (1.6pp)	+4pp (1.7pp)	+5.5pp (1.8pp)	+6pp (2.2pp)
Add Daily Temperature	-4.4pp (4pp)	-4.7pp (5pp)	-1.3pp (1.7pp)	-1.4pp (1.8pp)
Add All	+4pp (8.1pp)	+15.1pp (16.3pp)	-4.4pp (2.6pp)	-0.9pp (7.1pp)

Note:
Rows 2-6 show the difference in welfare between our base model and a model with the listed attribute for the median GCM. Values in parentheses are the standard deviation across all 17 GCMs. All results use the SSP-2 growth rates for baseline growth.

32

4.4 Aggregate Impacts of Climate Change in the Full Model

Figure 7 shows the effects of future climate change on welfare in our full model with all structural attributes, as well as with market-based adaptation. The left panel shows that all US states gain, with a population-weighted average effect of 19%. The largest welfare gains are in the upper Midwest. All states gain because forward-looking households can move to areas of the United States that will be more productive and have better amenities under climate change.

The right panel of Figure 7 shows the welfare impacts outside the US. The global average welfare impact, including the US, is a loss of 10.3%. Compared to Figure 6, 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 small effects on aggregate welfare, it significantly amplifies the unequal impacts across rich and poor countries indicating that omitting these structural economic features will understate the distributional impacts of climate change.

4.4.1 Reallocation in the United States

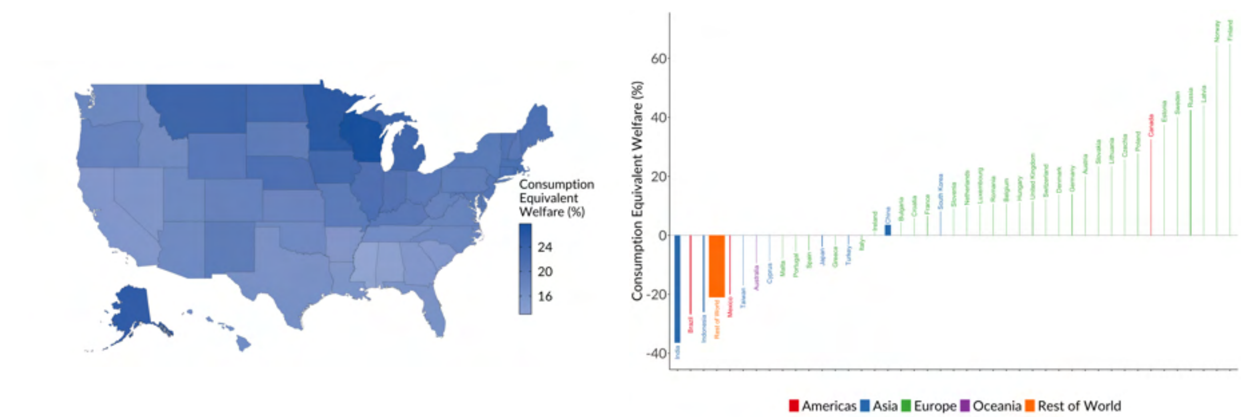
Figure 8 shows how labor reallocates within the US in response to climate change. The left panel shows the change in population shares for each state. In response to the heterogeneous impacts across space, households migrate from the South and West to the Midwest, New England, and Alaska. The populations of Alaska, Wisconsin, and Minnesota grow the most, while California, Texas, Florida, and the Atlantic coast experience the most out-migration.

The right panel shows the change in employment shares across different industries in the US. First, we project an overall increase in labor supply by over 2 percentage points. We project substantial increases in the employment shares in agriculture, as well as finance and insurance, and education. Other countries tend to have more severe damages to their agricultural sector, giving the US an increasing comparative advantage and boosting employment. The manufacturing sector experiences almost uniform declines in employment, continuing current structural trends in the US. Moreover, service sectors that tend to be downstream of manufacturing such as wholesale trade also tend to have employment losses because of propagation of shocks through input-output linkages. Section F.2 in the appendix shows the time trends of reallocation for each US state and industry, and shows how the trends depend on whether we account for alternative adaptation mechanisms, forward-looking behavior, or industrial damage heterogeneity.

4.5 Benefits of Market-Based Adaptation

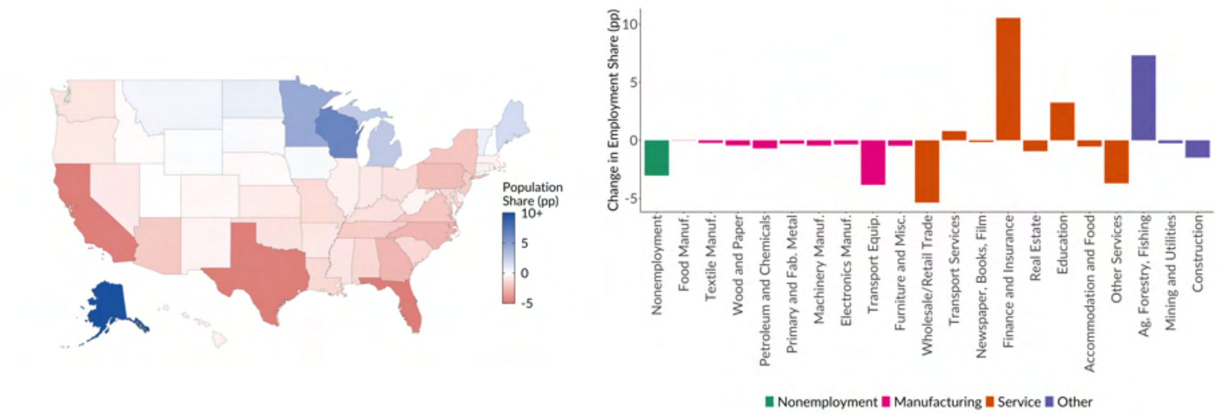
We now quantify the benefits of market-based adaptation to understand its role in US welfare gains. We consider three endogenous responses to changes in climate: changing trade shares, changing migration shares, and changing industry switching shares. As explained in appendix Section E.3,

Figure 7: US welfare and population effects with full model structure and market-based adaptation: 2015–2100.



Note: Left: the welfare impact of climate change as a percent of consumption averaged over the households in each state at the initial year.
Right: panel is the same but for other countries.
All non-US countries have no migration, and costless industry switching due to data limitations on the labor distribution, and they do not have welfare impacts from amenities since the amenity response function was estimated on US data at the state-level. The right panel shows the difference between state employment shares in the baseline economy with climate change for 2015-2100, and simulated state employment shares in a counterfactual scenario where the annual temperature distribution for each location was held constant at its 2015 level for 2015–2100. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals ($\dot{Z}^k_{i,t} = 1$ for all i, k) to allow the full impacts of the shocks to unfold. Both maps correspond to our full model with productivity shocks, amenity shocks, local structures, input-output loops, and heterogeneous response functions across industries. Both maps show results for the median welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

Figure 8: US welfare and population effects with full model structure and market-based adaptation: 2015–2100.



Note: Left: The difference between state employment shares in the baseline economy with climate change for 2015-2100, and simulated state employment shares in a counterfactual scenario where the annual temperature distribution for each location was held constant at its 2015 level for 2015–2100.

Right: The difference between industry employment shares in the baseline economy with climate change for 2015-2100, and simulated industry employment shares in a counterfactual scenario where the annual temperature distribution for each location was held constant at its 2015 level for 2015–2100.

Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals ($\dot{Z}^k_{i,t} = 1$ for all i, k) to allow the full impacts of the shocks to unfold. Both maps correspond to our full model with productivity shocks, amenity shocks, local structures, input-output loops, and heterogeneous response functions across industries. Both maps show results for the median welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

we quantify the role of adaptation by computing the welfare outcome under the full model with the adaptation channel versus the full model without it.

Table 2 reports welfare effects for the three adaptation mechanisms. 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 is:

$$\Delta_f^A \coloneqq \delta_f^{+A} - \delta_f.$$

Column 1 reports the level of US welfare in the full model without market-based adaptation: 4.7%. Columns 2–8 show the difference in US welfare in models where we turn on different combinations of adaptation mechanisms relative to the first column. Adaptation through changing trade shares alone improves US welfare by 3.9pp.[23] Changes in industry switching shares improves welfare by 2.1pp, while changes in within-US migration has the smallest effect, improving welfare by only 1.8pp. Adaptation through both labor market mechanisms improves welfare by 1.8pp, suggesting they are highly substitutable adaptation mechanisms. The last three columns show that trade and either labor reallocation channel are superadditive and interact. The headline number is that all three adaptation channels combined improve welfare by 15pp, amplifying the US welfare impacts more than fourfold. This complementarity indicates that forward-looking labor reallocation lets households better take advantage of adjustments through trade.

[23] Globally, trade adaptation improves welfare by 4pp.

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

Full Structure Welfare	Add Trade Adjustments	Add Migration	Add Industry Switching	Add Migration and Industry Switching	Add Trade and Migration	Add Trade and Industry Switching	Add All
4.7% (8.9%)	+3.9pp (4.9pp)	+1.8pp (1.3pp)	+2.1pp (2pp)	+1.8pp (1.4pp)	+12.3pp (9.8pp)	+13pp (9.5pp)	+15pp (12.7pp)

Note:
Each row shows the difference in welfare between our full model without market-based adaptation, and a model with the listed adaptation mechanism for the median GCM values in parentheses are the standard deviation across all 17 GCMs. All results use the SSP-2 growth rates for baseline growth.

Figure 9 shows the spatial distribution of welfare effects of adaptation. The first four panels correspond to Columns 2, 3, 4, and 8 of Table 2, and the last panel plots the total interaction or complementarity effect: the difference between Column 8 and the sum of Columns 2, 3, and 4. The population-weighted average value across all states in the figure corresponds to the values reported in the table.

The top left map shows the welfare value of trade adjustments. Trade makes Northern US states better off by substantial margins, with the largest gains in the Northeast and Midwest. Trade allows Northern states, which are generally neutral or better off under climate change even without trade, to adjust consumption patterns and purchase products from lower-cost sources.

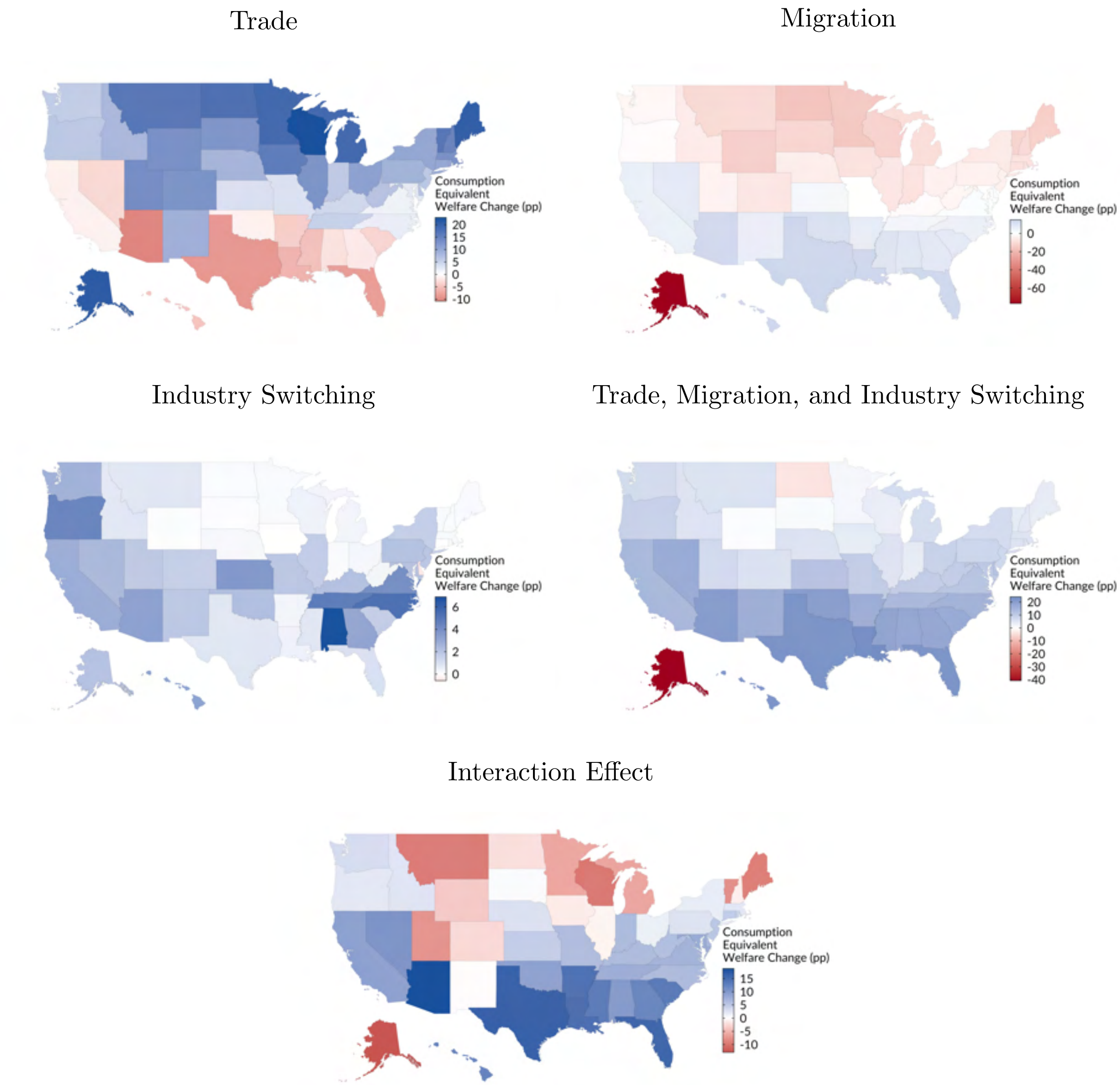
The South is actually worse off when trade can adjust, but labor cannot reallocate in response to climate change. When trade patterns can adjust, the additional extreme heat in the South substantially decreases the probability that these sellers are lowest-cost — effectively increasing export competition 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. In Section F.3 of the appendix we decompose this into a pure export 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, Midwestern and Northeastern states are made worse off because negatively affected households from other states migrate in and depress real wages for incumbent households. Households outside the Midwest are better off because they can migrate to the Midwest, Northeast, or Alaska which have higher productivity growth 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 moderate gain.

The middle left map shows the welfare value of industry switching. Industry switching improves welfare in almost all states. The largest gains in welfare from industry switching are concentrated in the Central and Southeastern US. These regions satisfy a combination of two criteria. First, the states in the South experience the greatest increase in extreme temperatures, reducing growth on average more than other states. Second, these states all tend to have a large initial share of workers in highly sensitive industries, making the ability to switch into less sensitive industries particularly valuable. For example, relative to other states, Alabama has a higher share of workers in the wood manufacturing, machinery manufacturing, and furniture manufacturing industries which tend to be especially sensitive to heat. Similarly, South Carolina has large shares in the sensitive electronics industry. Compare this to a state with low industry switching value like Delaware which initially has a large share of the population in the relatively non-climate sensitive service industries, or Michigan which has large shares of workers in machinery, electronics, and furniture manufacturing, but is in a climate that is initially cold.

The first three panels show that the three adaptation mechanisms all generate different spatial distributions of welfare impacts, and different levels of impacts. The middle right panel shows the

Figure 9: Welfare value of adaptation mechanisms: 2015–2100.



Note: Each state is colored according to its state-specific Δ^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 fixed at their no climate change trajectories. The middle left panel holds industry switching shares fixed at their no climate change trajectories. The middle right panel holds all three fixed at their no climate change trajectories. The bottom panel is the difference between the middle right panel and the sum of the remaining three. The welfare numbers for each state in the top four panels are computed identically to columns 2, 3, 4, and 8 in Table 2 and the population-weighted average across all states matches the values in the Table. The counterfactual scenario is if the annual temperature distribution for each location was held constant at its 2015 level for 2015–2100. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals ($\dot{Z}_{i,t}^{k} = 1$ for all i, k) to allow the full impacts of the shocks to unfold. All maps correspond to our full model with productivity shocks, amenity shocks, local structures, input-output loops, and heterogeneous response functions across industries. All maps show results for the median welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

effect of all three mechanisms combined. Every state but Alaska and North Dakota is better off when able to adapt through trade and the labor market. Alaska is significantly worse off because of market-based adaptation, with a welfare loss of about 40pp. 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 20pp 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 even 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 -0.38.[24]

The bottom map pulls out the complementarity effect between the adaptation mechanisms: the welfare impact of full adaptation in the bottom right map minus the sum of the individual adaptation benefits in the other three maps. If there were no interactions between the adaptation margins and they were neither complements nor substitutes then this map would show zeros everywhere. The interaction of the different mechanisms generally amplifies the effect of adaptation. The South gains from adaptation largely because of how trade interacts with labor market reallocation. Without labor market reallocation, trade makes the South worse off, but with labor market reallocation, Southern households can migrate North and take advantage of the North's trade benefits plotted in the top left map. The interactions have the opposite effect and exacerbate pecuniary externalities on incumbent households in the North.

4.6 Model Validation

Our quantitative results consist of three main findings. First, climate change impacts through productivity growth and amenities will severely reduce global welfare, but with major differences across countries.[25] The negative effects will tend to be borne by lower-income countries, while richer countries will tend to gain. Second, the US will gain from climate's impacts on growth and amenities. The US's welfare gain is driven by a combination of benefits from reallocation through trade and labor adjustments, workers dynamically adjusting to future climate change, and positive impacts being amplified by the economy's input-output network. Third, market based adaptation has an outsized influence on welfare. In the US, adaptation quadruples the total US welfare impact, 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 growth and local amenities — are a

[24] Damages tend to be regressive: the correlation between the negative impacts of climate change and state income in 2015 is -0.41.

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

good fit to reality. We validate our structural model by doing an apples-to-apples comparison to predicted welfare impacts from our reduced form approach. Equation (6) allows us to estimate the welfare impact of a location-time specific change in climate — which we call a local change in climate — but not a change in a climate variable that is common across all regions because of the time fixed effect. For transparency, we perform the simplest comparison where we shock regions *individually* with their projected change in climate under all 17 GCMs. We do this using both our reduced form model and the full quantitative model with market-based adaptation and then compare the estimated welfare results.

Figure 10 plots a 50 bin binscatter of the quantitative results against the reduced form results. Three points stand out. First, the best linear fit line is almost precisely 1 which means that, on average, cross-region differences in welfare in the reduced form model match that of the quantitative model. This gives us confidence that the distribution of our findings across locations is accurate. Second, the correlation of the relationship is 0.4 indicating that the fit between the two approaches is relatively good. Last, on average, the quantitative welfare estimates are about 9pp 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 a mis-calibration of a model parameter like a trade elasticity, or the assumption of perfect information households. 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.

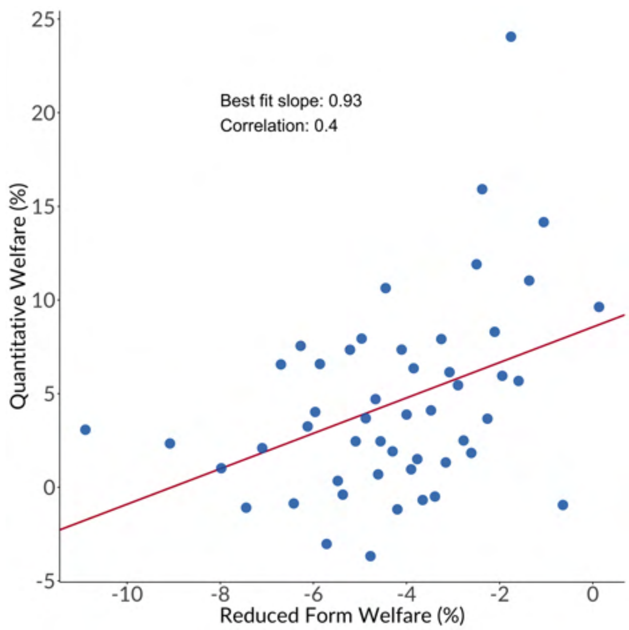
5 Conclusion

In this paper we develop two approaches for evaluating the economics of climate change in dynamic spatial equilibrium. In our first approach we show how observable migration data allows 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.

In our second approach we add significantly more assumptions and structure by building a dynamic spatial quantitative model. 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. We find that allowing trade or labor to reallocation has moderate positive effects on US welfare, but the complementarities between the two lead to substantially greater gains when both can reallocate together. 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

Figure 10: Reduced form welfare versus structural welfare.



50 point binscatter of the structural/quantative model's welfare predictions for each US state versus the reduced form model's welfare predictions. We generate the welfare results for both models by shocking each country individually with one of the 17 GCM's RCP 4.5 temperature trajectories. The structural model is our full model with amenities, heterogeneous industry responses, input-output loops, forward-looking US households, and market-based adaptation in response to climate change. The data are generated using 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

mechanisms at 20% 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 growth and on household utility. Our model shows that in spatial equilibrium, growth effects are well-identified by regressing growth in bilateral trade flows normalized by growth in a country's own expenditures on temperature, growth in trade costs, and growth in input prices. Data on time-varying trade costs like tariffs and input costs like wages are generally easy to obtain making our approach an attractive alternative to standard approaches. 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. Our approach to estimating productivity effects circumvents hidden issues in empirical models that ignore spatial linkages. In addition to the extensive literature emphasizing the importance of dynamic behavior for identifying the effect of climate change, 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.

Third, we provide a roadmap for future 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 allow us to evaluate welfare and 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 reduced form model solely focused on the effect of a local change in climate, however our quantitative model makes clear that changes in climate elsewhere in the globe also matter for welfare because of input-output linkages and market reallocation. Future work can use the reduced form approach to better understand the welfare spillovers from climate change elsewhere without needing to take a stand on economic geography or how markets are linked. 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.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012) "The Network Origins of Aggregate Fluctuations," *Econometrica*, Vol. 80, No. 5, pp. 1977–2016.

Albouy, David, Walter Graf, Ryan Kellogg, and Hendrik Wolff (2016) "Climate amenities, climate change, and American quality of life," *Journal of the Association of Environmental and Resource Economists*, Vol. 3, No. 1, pp. 205–246.

Anderson, Simon P, André De Palma, and J-F Thisse (1988) "A representative consumer theory of the logit model," *International Economic Review*, pp. 461–466.

Artuc, Erhan, Shubham Chaudhuri, and John McLaren (2010) "Trade Shocks and Labor Adjustment: A Structural Empirical Approach," *The American Economic Review*, Vol. 100, No. 3, pp. 1008–1045.

Auffhammer, Maximilian, Solomon M Hsiang, Wolfram Schlenker, and Adam Sobel (2013) "Using weather data and climate model output in economic analyses of climate change," *Review of Environmental Economics and Policy*, Vol. 7, No. 2, pp. 181–198.

Bakkensen, Laura and Lint Barrage (2021) "Climate shocks, cyclones, and economic growth: bridging the micro-macro gap."

Balboni, Clare Alexandra (2019) "In harm's way? infrastructure investments and the persistence of coastal cities."

Baldos, Uris LC, Thomas W Hertel, and Frances C Moore (2019) "Understanding the Spatial Distribution of Welfare Impacts of Global Warming on Agriculture and Its Drivers," *American Journal of Agricultural Economics*, Vol. 101, No. 5, pp. 1455–1472.

Baqaee, David Rezza and Emmanuel Farhi (2020) "Productivity and Misallocation in General Equilibrium," *Quarterly Journal of Economics*, Vol. 135, No. 1, pp. 105–163.

Bigio, Saki and Jennifer La'o (2020) "Distortions in production networks," *Quarterly Journal of Economics*, Vol. 135, No. 4, pp. 2187–2253.

Burke, Marshall, Melanie Craxton, Charles D Kolstad, Chikara Onda, Hunt Allcott, Erin Baker, Lint Barrage, Richard Carson, Kenneth Gillingham, Josh Graff-Zivin et al. (2016) "Opportunities for advances in climate change economics," *Science*, Vol. 352, No. 6283, pp. 292–293.

Burke, Marshall and Kyle Emerick (2016) "Adaptation to Climate Change: Evidence from US Agriculture," *American Economic Journal: Economic Policy*, Vol. 8, No. 3, pp. 106–140.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel (2015) "Global non-linear effect of temperature on economic production," *Nature*, Vol. 527, No. 7577, pp. 235–239.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro (2019) "Trade and Labor Market Dynamics," *Econometrica*, Vol. 87, No. 3, p. 741–835.

Caliendo, Lorenzo and Fernando Parro (2015) "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, Vol. 82, No. 1, pp. 1–44.

Carleton, Tamma A and Solomon M Hsiang (2016) "Social and economic impacts of climate," *Science*, Vol. 353, No. 6304, p. aad9837.

Carleton, Tamma A, Amir Jina, Michael T Delgado, Michael Greenstone, Trevor Houser, Solomon M Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan B Nath et al. (2021) "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits."

Carvalho, Vasco M., Makoto Nirei, Yukiko U. Saito, and Alireza Tahbaz-Salehi (2021) "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," Vol. 136, No. 2, pp. 1255–1321.

Carvalho, Vasco M. and Alireza Tahbaz-Salehi (2019) "Production Networks: A Primer," *Annual Review of Economics*, Vol. 11, No. December, pp. 635–663.

Center for International Earth Science Information Network (2018) "Documentation for the Gridded Population of the World, Version 4 (GPWv4), Revision 11 Data Sets.."

Colacito, Ric, Bridget Hoffmann, and Toan Phan (2018) "Temperatures and growth: A panel analysis of the United States," *Journal of Money, Credit, and Banking*, Vol. 51, No. 2-3, p. 2019.

Conte, Bruno, Klaus Desmet, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg (2020) "Local sectoral specialization in a warming world."

Costinot, Arnaud, Dave Donaldson, and Cory Smith (2016) "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World," *Journal of Political Economy*, Vol. 124, No. 1, pp. 205–248.

Cruz, Jose Luis (2021) "Global Warming and Labor Market Reallocation."

Cruz, Jose Luis and Esteban Rossi-Hansberg (2021) "The Economic Geography of Global Warming."

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken (2012) "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, Vol. 4, No. 3, pp. 66–95.

Deryugina, Tatyana and Solomon Hsiang (2017) "The marginal product of climate."

Deschênes, Olivier and Michael Greenstone (2007) "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, Vol. 97, No. 1, pp. 354–385.

Desmet, Klaus, Robert E. Kopp, Scott A. Kulp, Dávid Krisztián Nagy, Michael Oppenheimer, Esteban Rossi-Hansberg, and Benjamin H. Strauss (2021) "Evaluating the Economic Cost of Coastal Flooding," *American Economic Journal: Macroeconomics*, Vol. 13, No. 2, pp. 444–86.

Desmet, Klaus and Esteban Rossi-Hansberg (2015) "On the spatial economic impact of global warming," *Journal of Urban Economics*, Vol. 88, pp. 16–37.

Dietz, Simon and Nicholas Stern (2015) "Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions," *The Economic Journal*, Vol. 125, No. 583, pp. 574–620.

Diffenbaugh, Noah S and Marshall Burke (2019) "Global warming has increased global economic inequality," *Proceedings of the National Academy of Sciences*, Vol. 116, No. 20, pp. 9808–9813.

Eaton, Jonathan and Samuel Kortum (2002) "Technology, Geography, and Trade," *Econometrica*, Vol. 70, No. 5, pp. 1741–1779.

Fried, Stephie (2021) "Seawalls and stilts: A quantitative macro study of climate adaptation," Federal Reserve Bank of San Francisco.

Gouel, Christophe and David Laborde (2021) "The crucial role of domestic and international market-mediated adaptation to climate change," *Journal of Environmental Economics and Management*, Vol. 106, p. 102408.

Guo, Christopher and Christopher Costello (2013) "The value of adaption: Climate change and timberland management," *Journal of Environmental Economics and Management*, Vol. 65, No. 3, pp. 452–468.

Hotz, V Joseph and Robert A Miller (1993) "Conditional choice probabilities and the estimation of dynamic models," *The Review of Economic Studies*, Vol. 60, No. 3, pp. 497–529.

Hsiang, Solomon (2016) "Climate Econometrics," *Annual Review of Resource Economics*, Vol. 8, No. 1, pp. 43–75.

Jones, Benjamin F and Benjamin A Olken (2010) "Climate shocks and exports," *American Economic Review*, Vol. 100, No. 2, pp. 454–59.

Lemoine, Derek (2021) "Estimating the Consequences of Climate Change from Variation in Weather," *NBER Working Paper*, No. w25008.

Mendelsohn, Robert, William D Nordhaus, and Daigee Shaw (1994) "The impact of global warming on agriculture: a Ricardian analysis," *The American economic review*, pp. 753–771.

Mérel, Pierre and Matthew Gammans (2018) "Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation?" *American Journal of Agricultural Economics.*

Miller, Steve, Kenn Chua, Jay Coggins, and Hamid Mohtadi (2021) "Heat Waves, Climate Change, and Economic Output," *Journal of the European Economic Association.*

Missirian, Anouch and Wolfram Schlenker (2017) "Asylum applications respond to temperature fluctuations," *Science*, Vol. 358, No. 6370, pp. 1610–1614.

Moore, Frances C and Delavane B Diaz (2015) "Temperature impacts on economic growth warrant stringent mitigation policy," *Nature Climate Change*, Vol. 5, No. 2, p. 127.

Mullins, Jamie T and Prashant Bharadwaj (2021) "Weather, Climate, and Migration in the United States," *NBER Working Paper 28614.*

Nath, Ishan B (2020) "The Food Problem and the Aggregate Productivity Consequences of Climate Change."

Newell, Richard G, Brian C Prest, and Steven E Sexton (2021) "The GDP-temperature relationship: Implications for climate change damages," *Journal of Environmental Economics and Management*, p. 102445.

Ortiz-Bobea, Ariel, Toby R Ault, Carlos M Carrillo, Robert G Chambers, and David B Lobell (2021) "Anthropogenic climate change has slowed global agricultural productivity growth," *Nature Climate Change*, Vol. 11, No. 4, pp. 306–312.

Politico (2021) *Regulators refuse to step in as workers languish in extreme heat*: Politico.

Schlenker, Wolfram and Michael J Roberts (2009) "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of sciences*, Vol. 106, No. 37, pp. 15594–15598.

Silva, JMC Santos and Silvana Tenreyro (2006) "The log of gravity," *The Review of Economics and statistics*, Vol. 88, No. 4, pp. 641–658.

The New Republic (2021) *Climate Change Is Killing My Old Summer Job*: The New Republic.

The New York Times (2020) *The great climate migration*: New York Times Magazine.

——— (2021) *European Steel Plan Shows Biden's Bid to Merge Climate and Trade Policy*: New York Times Magazine.

The Washington Post (2021) *How climate change and extreme weather are crimping America's pie supply*: The Washington Post.

Timmer, Marcel P, Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J De Vries (2015) "An illustrated user guide to the world input–output database: the case of global automotive production," *Review of International Economics*, Vol. 23, No. 3, pp. 575–605.

Appendices

A Industry List

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

NAICS 11: Agriculture, Forestry, Fishing, and Hunting
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
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 GCM List

Here we list the set of 17 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

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 better match the data available for the counterfactual simulations.

We integrate our economic data with temperature and precipitation data from Princeton's Global Meteorological Forcing Dataset (GMFD) for land surface modeling.[26] 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 counterfactual 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 U.S. Commodity Flow Survey, the 2012 American Community Survey, and the U.S. 2012 Current Population Survey. 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.

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 the 2012 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.

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

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 2000 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 Initial Distribution of Labor

We use the 2000 Census to construct the initial distribution of labor. We include individuals between 25 and 65.[27]

C.2.9 Migration Shares

We use annual data on migration across states from the Public Use Micro Sample (PUMS) of the American Community Survey (ACS) 2000-2014, and monthly data on migration across sectors using Current Population

[27] Vermont has one industry with no reported employment in the ACS so we insert a value of 1 rather than omit it entirely.

Survey (CPS) 2000-2014 to construct an annual transition matrix across markets following the method in CDP.

D Derivation of Estimating Equations and Comparison to Alternative Approaches

In this appendix we derive our 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

Recall that from equations (16) and (17) we can write the expenditures of region n on industry k goods from region i as:

$$X^k_{ni,t} = \left(\Gamma^k\right)^{-\theta^k} \frac{Z^k_{i,t}\left(x^k_{i,t}\right)^{-\theta^k}\left(\tau^k_{ni,t}\right)^{-\theta^k}}{\left(P^k_{n,t}\right)^{-\theta^k}} X^k_{n,t}.$$

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

$$\frac{X^k_{ni,t}}{X^k_{nn,t}} = \frac{Z^k_{i,t}\left(x^k_{i,t}\right)^{-\theta^k}\left(\tau^k_{ni,t}\right)^{-\theta^k}}{Z^k_{n,t}\left(x^k_{n,t}\right)^{-\theta^k}}.$$

Dividing by its lag, using equation (15) to substitute in for the Z^k terms, and taking the logarithm on both sides and rearranging we obtain:

$$\log\left(\frac{X^k_{ni,t}/X^k_{nn,t}}{X^k_{ni,t-1}/X^k_{nn,t-1}}\right) = \left[g(\mathbf{T}_{i,t};\zeta^k_{\mathbf{Z}}) - g(\mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}})\right] + \log\left(\frac{1+\wp^k_{i,t}}{1+\wp^k_{n,t}}\right)$$
$$- \theta^k \log\left(\frac{\tau^k_{ni,t}}{\tau^k_{ni,t-1}}\right) - \theta^k \log\left(\frac{x^k_{i,t}}{x^k_{i,t-1}}\Big/\frac{x^k_{n,t}}{x^k_{n,t-1}}\right)$$

which matches equation (3.1).

D.2 Derivation of Estimating Equation for Effects of Temperature on Utility

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 (2), which may alternatively be expressed as:

$$V^k_{n,t} = \underbrace{U\left(C^k_{n,t}, B_{n,t}\right)}_{\text{instantaneous utility}} + \underbrace{\beta\mathbb{E}_t(V^k_{n,t+1})}_{\text{base value staying in market}} + \underbrace{\mathbb{E}_\epsilon\left[\max_{\{i,s\}^{N,K}_{i=1,s=0}}\left\{\nu\epsilon^s_{i,t} + \nu\bar{\epsilon}^{ks}_{ni,t}\right\}\right]}_{\text{option value of moving markets}} \tag{25}$$

where $V^k_{n,t} \equiv \mathbb{E}_\epsilon\left[v^k_{n,t}\right]$ and:

$$\bar{\epsilon}^{ks}_{ni,t} \equiv \frac{1}{\nu}\left[\beta\mathbb{E}_t\left(V^s_{i,t+1} - V^k_{n,t+1}\right) - \mu^{ks}_{ni}\right] \tag{26}$$

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

Equation (26) is analogously the difference in idiosyncratic shocks $\epsilon^k_{n,t} - \epsilon^s_{i,t}$ 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 (25) yields the Euler equation:

$$
\begin{aligned}
\nu\bar{\epsilon}^{ks}_{ni,t} + \mu^{ks}_{ni} &= \beta\mathbb{E}_t\left(V^s_{i,t+1} - V^k_{n,t+1}\right) \\
&= \beta\mathbb{E}_t\left[U(C^s_{i,t+1}, B_{i,t+1}) - U(C^k_{n,t+1}, B_{n,t+1}) + \mathbb{E}_{t+1}\left(V^s_{i,t+2} - V^k_{n,t+2}\right) + \Omega(\bar{\epsilon}^{\mathbf{s}}_{\mathbf{i,t+1}}) - \Omega(\bar{\epsilon}^{\mathbf{k}}_{\mathbf{n,t+1}})\right] \\
&= \beta\mathbb{E}_t\left[U(C^s_{i,t+1}, B_{i,t+1}) - U(C^k_{n,t+1}, B_{n,t+1}) + \nu\bar{\epsilon}^{ks}_{ni,t+1} + \mu^{ks}_{ni} + \Omega(\bar{\epsilon}^{\mathbf{s}}_{\mathbf{i,t+1}}) - \Omega(\bar{\epsilon}^{\mathbf{k}}_{\mathbf{n,t+1}})\right]
\end{aligned} \tag{27}
$$

where:

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

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

As in Artuc et al. (2010), the Euler equation given by equation (27) 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 $\Omega(\bar{\epsilon}^{\mathbf{k}}_{\mathbf{n,t}})$ and the expected continuation value from moving $\bar{\epsilon}^{ks}_{ni,t}$ can be expressed as functions of only migration shares. Recall that the migration shares are given by equation (3):

$$
\pi^{ks}_{ni,t} = \frac{\exp\left[\left(\beta\mathbb{E}_t\left(V^s_{i,t+1}\right) - \mu^{ks}_{ni}\right)/\nu\right]}{\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta\mathbb{E}_t\left(V^h_{l,t+1}\right) - \mu^{kh}_{nl}\right)/\nu\right]}
$$

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

$$
\pi^{kk}_{nn,t} = \frac{\exp\left[\left(\beta\mathbb{E}_t\left(V^k_{n,t+1}\right)\right)/\nu\right]}{\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta\mathbb{E}_t\left(V^h_{l,t+1}\right) - \mu^{kh}_{nl}\right)/\nu\right]}.
$$

Taking logs, we obtain:

$$
\begin{aligned}
\log\pi^{kk}_{nn,t} &= \frac{1}{\nu}\beta\mathbb{E}_t\left(V^k_{n,t+1}\right) - \log\sum_{l=1}^{N}\sum_{h=o}^{K}\exp\left[\left(\beta\mathbb{E}_t\left(V^h_{l,t+1}\right) - \mu^{kh}_{nl}\right)/\nu\right] \\
\implies -\nu\log\pi^{kk}_{nn,t} &= \nu\log\left(\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta\mathbb{E}_t\left(V^h_{l,t+1} - V^k_{n,t+1}\right) - \mu^{kh}_{nl}\right)/\nu\right]\right) \equiv \Omega(\bar{\epsilon}^{\mathbf{k}}_{\mathbf{n,t}}).
\end{aligned} \tag{28}
$$

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, $\bar{\epsilon}^{ks}_{ni,t}$ can then be expressed as:

$$
\log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) = \frac{\beta}{\nu}\mathbb{E}_t\left(V^s_{i,t+1} - V^k_{n,t+1}\right) - \frac{\mu^{ks}_{ni}}{\nu} \equiv \bar{\epsilon}^{ks}_{ni,t}. \tag{29}
$$

Finally, we derive the moment condition by substituting the expressions for $\Omega(\bar{\epsilon}^{\mathbf{k}}_{\mathbf{n,t}})$ and $\bar{\epsilon}^{ks}_{ni,t}$, given by equations (28) and (29) respectively, into the Euler equation in equation (27):

$$\nu\bar{\epsilon}^{ks}_{ni,t} + \mu^{ks}_{ni} = \beta\mathbb{E}_t\left[U(C^s_{i,t+1}, B_{i,t+1}) - U(C^k_{n,t+1}, B_{n,t+1}) + \nu\bar{\epsilon}^{ks}_{ni,t+1} + \mu^{ks}_{ni} + \Omega(\bar{\epsilon}^{\mathbf{s}}_{\mathbf{i,t+1}}) - \Omega(\bar{\epsilon}^{\mathbf{k}}_{\mathbf{n,t+1}})\right]$$

$$\Longrightarrow \nu\log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) + \mu^{ks}_{ni} = \beta\mathbb{E}_t\left[\log\left(\frac{B_{i,t+1}}{B_{n,t+1}}\frac{C^s_{i,t+1}}{C^k_{n,t+1}}\right) + \nu\log\left(\frac{\pi^{ks}_{ni,t+1}}{\pi^{kk}_{nn,t+1}}\right) + \mu^{ks}_{ni} + \nu\log\left(\frac{\pi^{kk}_{nn,t+1}}{\pi^{ss}_{ii,t+1}}\right)\right]$$

$$\Longrightarrow \mathbb{E}_t\left[\frac{\beta}{\nu}\log\left(\frac{B_{i,t+1}}{B_{n,t+1}}\frac{C^s_{i,t+1}}{C^k_{n,t+1}}\right) + \beta\log\left(\frac{\pi^{ks}_{ni,t+1}}{\pi^{ss}_{ii,t+1}}\right) - \log\left(\frac{\pi^{ks}_{ni,t}}{\pi^{kk}_{nn,t}}\right) + \frac{\beta-1}{\nu}\mu^{ks}_{ni}\right] = 0.$$

Assuming perfect information and rearranging delivers equation (22).

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

Here we show analytically how standard partial equilibrium, static approaches for measuring the impacts of climate change are biased. We then show that this bias is significant quantitatively by deriving analogous estimating equations from our model, and then estimating them using the exact same data. Thus 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 Growth 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:

$$Y_{it} = a_{it}L^{\gamma}_{it}K^{(1-\gamma)}_{it}$$

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:

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

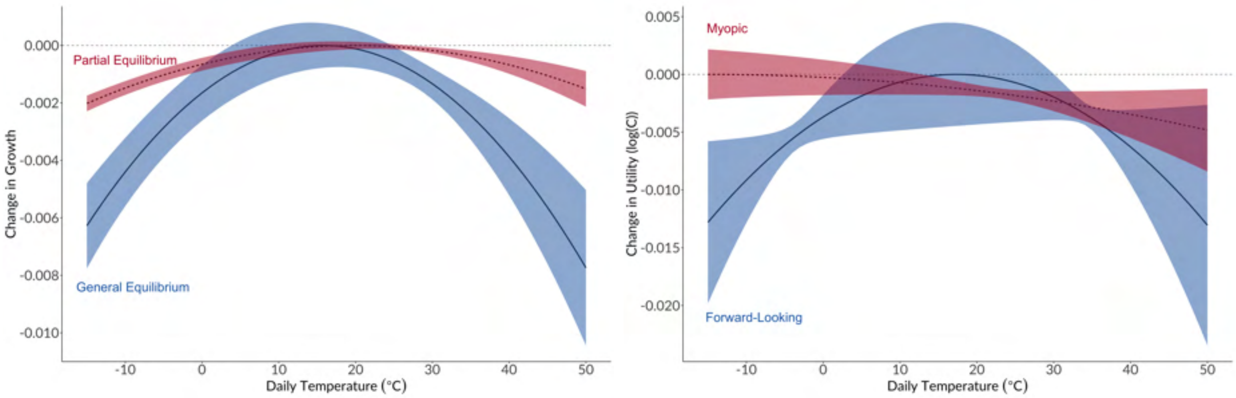
where the last term is constant recognizes that the capital to labor ratio is $(1-\gamma)/\gamma$ in equilibrium. Thus, regressing GDP per capita on a function of temperature and unit and time fixed effects to absorb $\bar{a}_{it}$ can identify the effect of temperature on productivity under the assumption that the remaining variation in temperature is not correlated with the error term. This approach is often used to also estimate effects of temperature on GDP growth by first-differencing the left hand side (Burke et al., 2015).

How does this compare to the analogous GDP specification generated by our general equilibrium model? Re-arranging equation (**??**), we can show that GDP growth can be written as:

$$\log\left(\frac{Y^k_{n,t}}{Y^k_{n,t-1}}\right) = g(\mathbf{T}_{n,t};\zeta^k_{\mathbf{Z}}) + \log\left(1+\wp^k_{n,t}\right) - \theta^k\log\left(\frac{x^k_{n,t}}{x^k_{n,t-1}}\right) - \theta^k\log\left(\frac{\Lambda^k_{n,t}}{\Lambda^k_{n,t-1}}\right). \tag{30}$$

GDP growth is a function of temperature, the base fundamental productivity growth rate, input costs, and firm market access. The important term here for identification in spatial equilibrium is growth in firm market

Figure A1: The effect of daily temperature on productivity growth using the GDP regression approach versus our general equilibrium approach (left) and on amenities using a dynamic versus static approach (right).



Left: The response functions are constructed using a second degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are Windsorized at -15°C and 50°C. The shaded area denotes the 95% confidence intervals. The solid response function is the same as in the left panel of Figure 3. The dashed response function is from the GDP regression in equation (30). The GDP estimating equation includes industry-country and industry-year fixed effects. Standard errors are clustered at the country level.
Right: The response functions are constructed using a second degree orthogonal polynomial approximation to the distribution of within-year daily temperatures. The temperature distributions are Windsorized at -15°C and 50°C. The shaded area denotes the 95% confidence intervals. The solid response function is the same as in the right panel of Figure 3. The dashed response function is from the static regression in equation (32). 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.

access growth $-\theta^k \log\left(\frac{\Lambda^k_{n,t}}{\Lambda^k_{n,t-1}}\right)$ where:

$$\Lambda^{-\theta^k}_{n,t} \equiv \sum_{i=1}^{N} \frac{(\tau_{in,t})^{-\theta^k} X_{i,t}}{\sum_{l=1}^{N} Z^k_{l,t}\left(x^k_{l,t}\tau^k_{il,t}\right)^{-\theta^k}}.$$

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 regional borders and affect GDP growth in n.

The central identification issue arises because temperature is positively correlated across space and this multilateral market access term is generally absorbed in the error term of climate impact specifications. Notice that n's market access term contains productivity for all other regions l: $Z^k_{l,t}$. Equation (15) shows that productivity in l is a function of l's temperature, which is in the error term and correlated with our variable of interest. These partial equilibrium approaches thus suffer from omitted variable bias.

Does this bias matter? The left panel of Figure A1 shows the estimated response function from the following specification in red:

$$\log\left(\frac{Y^k_{n,t}}{Y^k_{n,t-1}}\right) = g(\mathbf{T}_{n,t}; \zeta^k_{\mathbf{Z}}) + \delta^k_t + \phi^k_n + \varepsilon^k_{n,t} \tag{31}$$

where δ_t^k is an industry-year effect and ϕ_n^k is an industry-region effect. The primary difference between this specification and the literature is that our model delivers an equation in terms of GDP growth, not GDP per capita growth.

The response function still has the inverted-U shape as commonly found in the literature. There are, however, two key differences compared to our preferred response function in blue which matches Figure 3. First, the red response function is shifted right and peaks several degrees higher, over 20°C. Second, it is significantly flatter. Relative to the optimal temperature for each response function, the growth effect of a 50°C day is estimated to be only a third as harmful as our estimates. 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 growth and current productivity in each region. This then increases n's current market access $\Lambda_{n,t}^{-\theta^k}$, and market access growth because n's competitors now have lower productivity. According to equation (30), greater market access increases GDP growth so the error term will be positively correlated with n's temperature shock. By omitting market access growth from the estimating equation, we are attributing this effect to own-temperature and it gets picked up by our empirical estimates $\widehat{\zeta}_{\mathbf{Z}}^k$. Since the effect through market access is positive, the bias tends to flatten out the response function.

Dynamic Bias in Amenities Next we demonstrate that accounting for dynamics and forward-looking behavior significantly affects our amenity response function. With a myopic household we obtain following estimating equation:

$$\log\left(\frac{\pi_{ni,t}^{ks}}{\pi_{nn,t}^{kk}}\right) - \frac{1}{\nu}\log\left(\frac{\omega_{i,t}^{s}}{\omega_{n,t}^{k}}\right) = \frac{1}{\nu}\left[f(\mathbf{T_{i,t}} - \mathbf{T_{n,t}}; \zeta_{\mathbf{B}})\right] + \delta_t^k + \varphi_{ni}^k + \varepsilon_{ni,t}^{ks} \tag{32}$$

Since the household is myopic, the household only cares about differences in (now current) flow payoffs, and not continuation values captured by future migration. The right panel of Figure A1 shows the amenity response function from the myopic model in red and the dynamic model in blue.

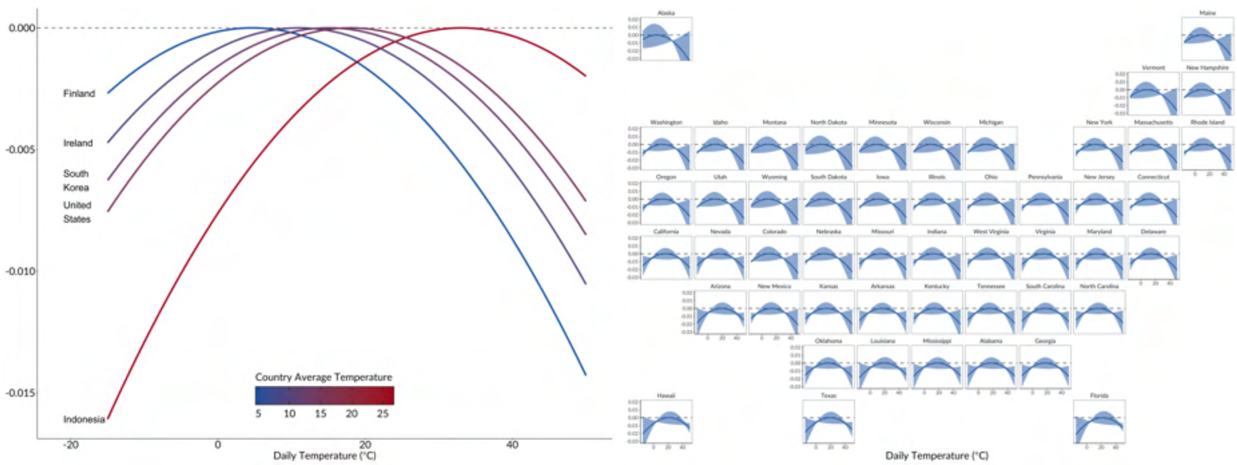
In our setting, ignoring forward-looking behavior shifts the response function to the left. Statistically, this arises because (1) temperature differences are strongly positively correlated over time, (2) and current temperature differences tend to be negatively correlated with future real wages differences. 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 (23). 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.

D.4 Reduced Form Representations of Adaptation in the Quantitative Response Functions

Figure A2: Productivity growth, amenities, and reduced form climate response functions under alternative polynomial and cubic spline approximations.

Productivity Growth by Average Temperature Amenities by Average Temperature



Note: The left panel shows the aggregate productivity growth response function for five countries when the response function is allowed to vary by a country's average temperature. The right panel shows the amenity response function for each state when the amenity response function is allowed to vary by a state's average temperature. Country/state-specific response functions are generated by estimating the same equations as in the main text, but where the response functions are also interacted with the country's/state's average temperature.

E Simulating and Decomposing the Impacts of Climate Change

In this appendix we provide details of 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.

E.1 Expressing and Solving the Model in Time Changes

Our first step is to express the model in time changes using hat algebra. 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 2 (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:*

$$\dot{x}_{n,t+1}^{k} = \left(\dot{L}_{n,t+1}^{k}\right)^{\gamma_n^k \psi_n} \left(\dot{w}_{n,t+1}^{k}\right)^{\gamma_n^k} \prod_{s=1}^{K} \left(\dot{P}_{n,t+1}^{k}\right)^{\gamma_n^{ks}} \tag{33}$$

$$\dot{P}_{n,t+1}^{k} = \left[\sum_{i=1}^{N} \lambda_{ni,t}^{k} \dot{Z}_{i,t+1}^{k} \left(\dot{x}_{i,t+1}^{k} \dot{\tau}_{ni,t+1}^{k}\right)^{-\theta^k}\right]^{\frac{1}{\theta^k}} \tag{34}$$

$$\dot{\lambda}_{ni,t+1}^{k} = \left(\frac{\dot{x}_{n,t+1}^{k} \dot{\tau}_{ni,t+1}^{k}}{\dot{P}_{n,t+1}^{k}}\right)^{-\theta^k} \dot{Z}_{n,t+1}^{k} \tag{35}$$

$$X_{n,t+1}^{k} = \sum_{s=1}^{K} \gamma_n^{ks} \sum_{i=1}^{N} \lambda_{in,t+1}^{k} X_{i,t+1}^{k} + \alpha^k \left(\sum_{k=1}^{K} w_{n,t+1}^{k} L_{n,t+1}^{k} + \iota_n \chi_{t+1}\right) \tag{36}$$

$$w_{n,t+1}^{k} L_{n,t+1}^{k} = \gamma_n^k \left(1 - \psi^k\right) \sum_{i=1}^{N} \lambda_{in,t+1}^{k} X_{i,t+1}^{k} \tag{37}$$

for all regions n and i, industries k and s at each time t, where $\chi_{t+1} = \sum_{i=1}^{N} \sum_{s=1}^{K} \frac{\psi_i}{1-\psi_i} w_{i,t+1}^{s} L_{i,t+1}^{s}$ and the exogenous time changes in productivities $\dot{Z}_{t+1}$ are given by equation (15).

Once we have the momentary equilibrium (i.e. production side of the economy) at each t using Proposition 2, we express the household side of the economy in time differences with the next proposition from CDP:

Proposition 3 (CDP)**.** *Define $u_{n,t}^{k} \equiv \exp(V_{n,t}^{k})$. 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:*

$$\dot{\pi}_{ni,t+1}^{ks} = \frac{\left(\dot{u}_{i,t+2}^{s}\right)^{\beta/\nu}}{\sum_{l=1}^{N} \sum_{h=0}^{K} \pi_{nl,t}^{kh} \left(\dot{u}_{l,t+2}^{h}\right)^{\beta/\nu}} \tag{38}$$

$$\dot{u}_{n,t+1}^{k} = \dot{B}_{n,t+1} \dot{\omega}_n^k(\dot{L}_{t+1}, \dot{Z}_{t+1}, \dot{\kappa}_{t+1}) \left(\sum_{i=1}^{N} \sum_{s=0}^{K} \pi_{ni,t}^{ks} \left(\dot{u}_{i,t+2}^{s}\right)^{\beta/\nu}\right)^{\nu} \tag{39}$$

$$L_{n,t+1}^{k} = \sum_{i=1}^{N} \sum_{s=0}^{K} \pi_{in,t}^{sk} L_{i,t}^{s} \tag{40}$$

for all regions n and i, industries k and s at each time t, where $\{\dot{\omega}_n^k(\dot{L}_t, \dot{Z}_t, \dot{\kappa}_t)\}_{n=1,k=0,t=1}^{N,K,\infty}$ 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 (7), 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 2 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 (changes in bold) 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 (33) and (34) 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 (33) and check whether the value of $\dot{P}^k_{n,t+1}$ from equation (34) 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 (35) and $\dot{P}^k_{n,t+1}$ to obtain $\lambda^k_{ni,t+1}$.

- **Step 4**: Use equation (36), $\lambda^k_{ni,t+1}$, 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 (37), $X^k_{n,t+1}$, 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 3 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 (38)].

- **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 (40)].

- **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 (39)]. 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.

E.2 Simulating the Full 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.

E.2.1 Climate Projections

To produce our counterfactual outcomes for the future simulations we use temperature projections from the Coupled Model Intercomparison Project (CMIP6), that correspond to specific Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs). Specifically, we use the SSP-2-4.5 scenario. This scenario corresponds to RCP4.5 which yields radiative forcing of 4.5 W/m^2 at the end of the century. 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. The change in temperature variance under this scenario is presented in Figure **??**.

E.2.2 Simulation Steps

Using these temperature projections, we compute the impacts of climate change by simulating forward our model assuming constant fundamentals, except for the impact of temperature on productivity growth and amenities[28]. 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:

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

The first component is the base growth rate $\left(1 + r_{i,t}^k\right)$ which we compute using the country-specific growth rates from the SSP-2 socioeconomic scenario which is recommended to be used alongside the RCP 4.5 warming scenario. The trajectories are plotted in the appendix in Figure A5. The second component is the impact of temperature on productivity growth. The temperature response function for productivity $g(\boldsymbol{T}_{i,t}; \zeta_{\mathbf{Z}})$ is estimated from historical data as outlined in Section 3.1 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 3.2, 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 appendix E.1 to solve the baseline economy[29]. We then extend the simulations to 2200 assuming $\dot{Z}_{i,t}^k = \dot{B}_{i,t}^k = 1$ after year 2100 to allow the economy to converge to a new steady state.

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

[29] Note that even though productivity is time varying, it is not identified by the data so we can simulate the economy using constant fundamentals. Also, since we are not using sufficient statistics to capture the evolution of fundamentals, the baseline future economy does not implicitly capture the climate shocks and we must shock the baseline economy ourselves.

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 SSP-2-4.5 scenario, relative to maintaining the year 2000 observed temperature distribution.

E.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 economic channels 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 three channels. 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 industry to be amplified and generate larger aggregate effects. 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.[30] These higher-order impacts impose additional costs on consumers on top of the costs from the originally affected industry.[31] We quantify the impact of these feedbacks by comparing results from an economy with input-output loops to one without 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 the two channels described below in a similar fashion.

The second channel is the importance of capturing local structures as a factor of production. Local structures are exogenously given, so to remove local structures we set the structures share of value added equal to zero: $\psi^k = 0$ for all k. The third channel is the importance of capturing climate impacts on local amenities. A significant portion of the climate impacts literature focuses only on climate's effects on production (e.g. Dell et al., 2012; Burke et al., 2015), but since amenities directly enter utility they may account for a larger share of climate change's overall welfare impact. To remove amenities, we set $B_{n,t} = 1$ in the utility function for all realizations of temperature.

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

[30] 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.

[31] In an economy like ours with log utility and a Cobb-Douglas production technology, the aggregate effect of a shock to some industry s on another industry k is given by the ksth element of the Leontief inverse of the economy $L = (I - A)^{-1}$ where A is the matrix of input-output coefficients γ_n^{ks} for all k, s.

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 shares, migration shares across regions, and industry switching 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 the labor market. 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.

E.3.1 Identifying Trade Adaptation

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

Proposition 4. *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:*

$$\dot{x}^k_{n,t+1} = \left(\dot{L}^k_{n,t+1}\right)^{\gamma^k_n \psi_n} \left(\dot{w}^k_{n,t+1}\right)^{\gamma^k_n} \prod_{s=1}^{K} \left(\dot{P}^k_{n,t+1}\right)^{\gamma^{ks}_n}, \tag{41}$$

$$\dot{P}^k_{n,t+1} = \left[\sum_{i=1}^{N} \overline{\lambda}^k_{ni,t} \dot{Z}^k_{i,t+1} \left(\dot{x}^k_{i,t+1} \dot{\tau}^k_{ni,t+1}\right)^{-\theta^k}\right]^{\frac{1}{\theta^k}}, \tag{42}$$

$$X^k_{n,t+1} = \sum_{s=1}^{K} \gamma^{ks}_n \sum_{i=1}^{N} \overline{\lambda}^k_{in,t+1} X^k_{i,t+1} + \alpha^k \left(\sum_{k=1}^{K} \dot{w}^k_{n,t+1} \dot{L}^k_{n,t+1} w^k_{n,t} L^k_{n,t} + \iota_n \chi_{t+1}\right), \tag{43}$$

$$w^k_{n,t+1} L^k_{n,t+1} = \gamma^k_n \left(1 - \psi^k\right) \sum_{i=1}^{N} \overline{\lambda}^k_{in,t+1} X^k_{i,t+1}, \tag{44}$$

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 4 together with Proposition 3 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 4) 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

E.3.2 Identifying Migration Adaptation

To identify adaptation in migration across regions and industry switching, we decompose migration shares across markets as follows:

$$\begin{aligned}\pi_{ni,t}^{ks} &= \frac{\sum_{h=0}^{K}\exp\left[\left(\beta\mathbb{E}_t\left(V_{i,t+1}^{h}\right)-\mu_{ni}^{kh}\right)/\nu\right]}{\sum_{l=1}^{N}\sum_{h=0}^{K}\exp\left[\left(\beta\mathbb{E}_t\left(V_{l,t+1}^{h}\right)-\mu_{nl}^{kh}\right)/\nu\right]}\cdot\frac{\exp\left[\left(\beta\mathbb{E}_t\left(V_{i,t+1}^{s}\right)-\mu_{ni}^{ks}\right)/\nu\right]}{\sum_{h=0}^{K}\exp\left[\left(\beta\mathbb{E}_t\left(V_{i,t+1}^{h}\right)-\mu_{ni}^{kh}\right)/\nu\right]}\\ &= \underbrace{\pi_{ni,t}^{k}}_{\substack{\text{migration}\\ \text{across regions}}}\cdot\underbrace{\pi_{ni,t}^{ks}|\pi_{ni,t}^{k}}_{\text{industry switching}}\end{aligned}$$

where $\pi_{ni,t}^{k}\equiv\sum_s\pi_{ni,t}^{ks}$ is the migration share across regions ni for workers originally in industry k, and $\pi_{ni,t}^{ks}|\pi_{ni,t}^{k}\equiv\frac{\pi_{ni,t}^{ks}}{\pi_{ni,t}^{k}}$ is the industry-switching share across industries ks amongst workers who were originally in industry k and migrated from region n to region i. Given this decomposition, we identify the role of adaptation in migration across regions and industry switching using the following proposition.

Proposition 5. *(i) Suppose that the exogenous trajectories of migration across regions $\{\pi_t^k\}_{t=0}^{\infty}$ and the time changes in fundamentals are known. Then the sequential competitive equilibrium in time changes* ***without adjustment in migration across regions*** *can be obtained from the following system of nonlinear equations:*

$$\dot{\pi}_{ni,t+1}^{ks}=\dot{\bar{\pi}}_{ni,t+1}^{k}\frac{\left(\dot{u}_{n,t+2}^{k}\right)^{\beta/\nu}}{\sum_{h=0}^{K}\pi_{ni,t}^{kh}\left(\dot{u}_{l,t+2}^{h}\right)^{\beta/\nu}} \tag{45}$$

$$\dot{u}_{n,t+1}^{k}=\dot{B}_{n,t+1}\dot{\omega}_n^k(\dot{L}_{t+1},\dot{Z}_{t+1},\dot{\kappa}_{t+1})\left(\sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{ni,t}^{ks}\left(\dot{u}_{i,t+2}^{s}\right)^{\beta/\nu}\right)^{\nu} \tag{46}$$

$$L_{n,t+1}^{k}=\sum_{i=1}^{N}\sum_{s=0}^{K}\pi_{in,t}^{sk}L_{i,t}^{s} \tag{47}$$

where $\{\dot{\omega}_n^k(\dot{L}_t,\dot{Z}_t,\dot{\kappa}_t)\}_{n=1,k=0,t=1}^{N,K,\infty}$ is the sequence of real wages that solves the momentary equilibrium (production side) in time changes given $\{\dot{L}_{t+1},\dot{Z}_{t+1},\dot{\kappa}_{t+1}\}_{t=1}^{\infty}$ [equations (33)-(37)], and the exogenous time changes in amenities are given by the time changes of equation (7).

(ii) Given exogenous trajectories of industry switching $\{\pi_{ni,t}\}_{t=0}^{\infty}$ and time changes in fundamentals, the sequential equilibrium in time changes ***without adjustment in industry switching*** *can be obtained by replacing equation (45) in (i) with:*

$$\dot{\pi}_{ni,t+1}^{ks}=\frac{\sum_{h=0}^{K}\pi_{ni,t}^{kh}\left(\dot{u}_{l,t+2}^{h}\right)^{\beta/\nu}}{\sum_{l=1}^{N}\sum_{h=0}^{K}\pi_{nl,t}^{kh}\left(\dot{u}_{l,t+2}^{h}\right)^{\beta/\nu}}\cdot\overline{\pi_{ni,t}^{ks}\dot{|}\pi_{ni,t}^{k}}. \tag{48}$$

For a given set exogenous trajectories of time changes in fundamentals, Proposition 5 generates equilibrium trajectories of the economy without the shares of migration across regions or shares of industry switching changing endogenously. In our simulations, we set the exogenous shares for migration across regions or industry switching to the path from the full model solution without climate change in our main results, following our method for isolating trade adaptation in the forward simulations described above. Comparing the equilibrium outcomes of this migration or industry switching-constrained economy against the outcomes from the full unconstrained model allows us to determine the role of adjustment in only migration or only industry switching.

Given Proposition 5, we can also examine the role of labor market adjustment across all markets (migration across regions and industry switching combined) using the following corollary:

Corollary 1. *Suppose that the trajectories of exogenously given migration 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* $\{\dot{\omega}_{n,t}^{k}\left(\dot{\overline{L}}_t, \dot{Z}_t, \dot{\tau}_t\right)\}_{t=0}^{\infty}$ *that solves equations (33)-(37) at each time t, where the exogenous trajectory of* $\dot{\overline{L}}_t$ *is constructed from the trajectory of baseline migration shares given.*

In this corollary, the intertemporal decisions of the household become completely exogenous because migration shares and industry switching are both made exogenous. With Proposition 5 and Corollary 1, we can quantify the role of adaptation in industry switching, migration across regions, or in both, without restricting the model to be one with no labor movement at all but rather one in which labor movement is restricted to the path it would have taken in the absence of climate change.

In particular, our procedure for identifying the role of migration adaptation (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 5) 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 migration adaptation

To tease out adaptation in migration across regions versus industry switching, we adopt a similar algorithm but alternatively hold only industry switching fixed at average levels across all regions, and only migration across regions fixed at average levels across all industries.

Table A1: The effect of daily temperature on productivity growth.

	(1)	(2)	(3)	(4)	(5)	(6)
First-Degree Orthog. Poly.	-0.003	-0.003	-0.004	-0.004	0.000	0.000
	(0.012)	(0.012)	(0.012)	(0.012)	(0.008)	(0.016)
Second-Degree Orthog. Poly.	-0.018**	-0.018**	-0.018**	-0.018**	-0.015***	-0.019*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)	(0.010)
Num.Obs.	422770	422770	422770	422770	422770	422770
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

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

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

F Additional Results

This section contains additional results and robustness checks.

Estimation Robustness Tables A1 and A2 show the robustness of our coefficient estimates for our productivity growth and 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 A3 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 1 which exactly matches the model-implied regression. The remaining columns increase the granularity of our fixed effects, with the last column having origin-industry-year and destination-industry fixed effects. Our estimates are highly robust.

Figure A3 plots several different estimates of our response functions. The left panels show the productivity growth 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 2–5, with our main specification in red. The bottom show estimates using cubic splines with 1–4 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 A2: The effect of daily temperature on amenities.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First-Degree Orthog. Poly.	0.022	-0.010	-0.029**	-0.001	-0.001	-0.000	0.004	-0.001
	(0.090)	(0.009)	(0.013)	(0.006)	(0.006)	(0.006)	(0.013)	(0.004)
Second-Degree Orthog. Poly.	-0.003	-0.026**	-0.098**	-0.032*	-0.031**	-0.033*	-0.062*	-0.022**
	(0.045)	(0.012)	(0.040)	(0.017)	(0.016)	(0.017)	(0.033)	(0.011)
Num.Obs.	50341	50341	50341	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	.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

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

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

A20

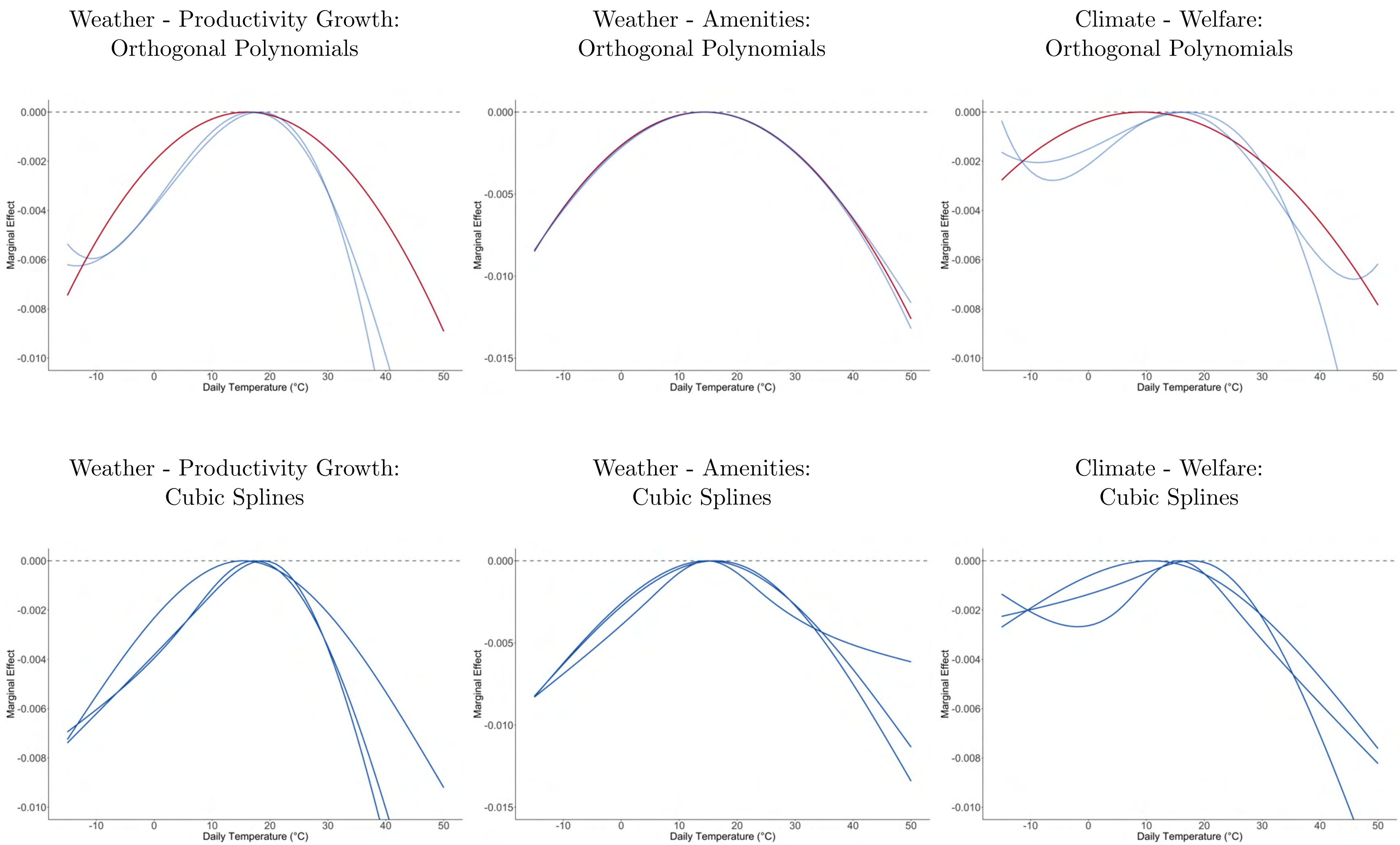
Table A3: The reduced form effect of climate on welfare.

	(1)	(2)	(3)	(4)	(5)
First-Degree Orthog. Poly.	-0.012***	-0.013***	-0.028***	-0.014***	-0.016***
	(0.003)	(0.003)	(0.006)	(0.003)	(0.004)
Second-Degree Orthog. Poly.	-0.007***	-0.007***	-0.017***	-0.008***	-0.009***
	(0.003)	(0.002)	(0.005)	(0.002)	(0.003)
Num.Obs.	101893	101893	101893	101893	101893
Destination FE	Yes	No	Yes	No	No
Origin FE	No	No	Yes	No	No
Industry FE	Yes	No	Yes	No	No
Year FE	Yes	No	Yes	No	No
Industry x Year FE	No	Yes	No	Yes	No
Dest x Industry FE	No	Yes	No	Yes	Yes
Orig x Industry FE	No	No	No	Yes	No
Orig x Industry x Year FE	No	No	No	No	Yes

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

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

Figure A3: Productivity growth, amenities, and reduced form climate response functions under alternative polynomial and cubic spline approximations.



Note: The top left panel shows the growth 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 growth response functions for 2 to 4 cubic splines. The bottom middle panel shows the amenity response functions for 2 to 4 cubic splines. The bottom right panel shows the reduced form climate response functions for 2 to 4 cubic splines.

A22

F.1 Additional Results

Table A4 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.

Table A5 shows the same results as Table 2 but where we shut down each adaptation channel.

Figure A4 plots the direct welfare effect of amenities (e.g. $\log\left(\widehat{B}_{i,t}\right)$), 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 10%.

Figure A5 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.

Table A4: 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	**4.7% (8.9%)**	**19% (8.9%)**	**-16.8% (5.2%)**	**-10.3% (6.4%)**
Remove Input-Output Linkages	-2.1pp (3.8pp)	-12.9pp (3.8pp)	+7.1pp (2.1pp)	+2.3pp (4.9pp)
Remove Amenities	+0.2pp (2.2pp)	-0.8pp (2.2pp)	+2.9pp (1pp)	+3.1pp (1.2pp)
Remove Forward-Looking US Households	-0.2pp (0pp)	-9.8pp (0pp)	+0pp (0pp)	-0.3pp (0.2pp)
Remove Industry Heterogeneity	-7.2pp (2.5pp)	-5.2pp (2.5pp)	-6.6pp (1.4pp)	-7.8pp (2.9pp)
Remove Daily Temperature	+6.5pp (7.3pp)	+3pp (7.3pp)	+1.7pp (2.5pp)	+1.6pp (3.6pp)
Remove All	-4pp (8.1pp)	-15.1pp (8.1pp)	+4.4pp (2.6pp)	+0.9pp (7.1pp)

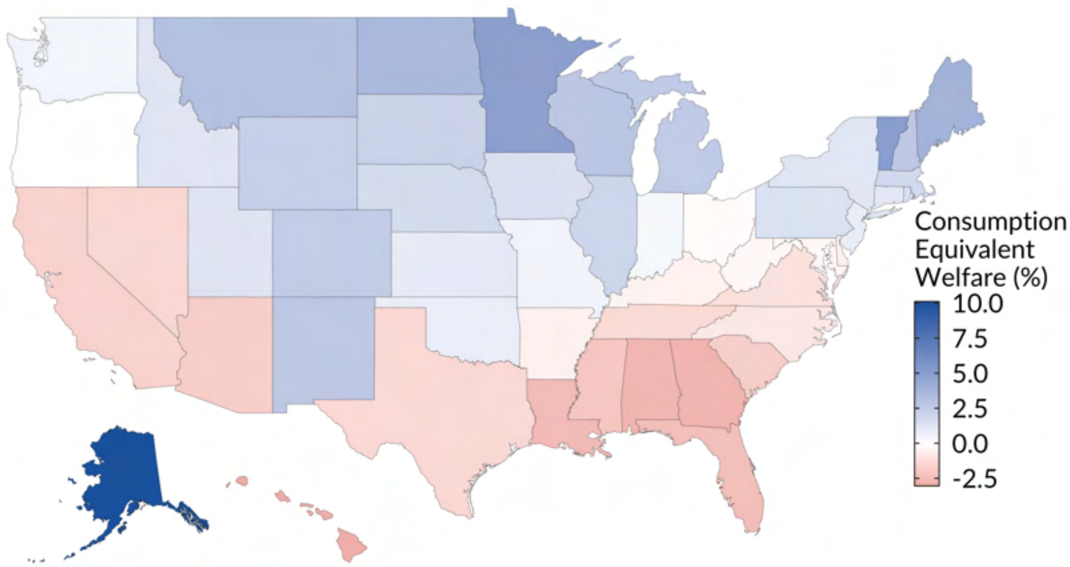
Note:
Rows 2-6 show the difference in welfare between our full model and a model without the listed attribute for the median GCM. Values in parentheses are the standard deviation across all 17 GCMs. All results use the SSP-2 growth rates for baseline growth.

Table A5: US welfare contribution of adaptation through trade, migration, and industry switching: 2015–2100.

Full Structure + Full Adaptation Welfare	Remove Trade Adjustments	Remove Migration	Remove Industry Switching	Remove Migration and Industry Switching	Remove Trade and Migration	Remove Trade and Industry Switching	Remove All
19% (8.9%)	-13.1pp (1.4pp)	-3.9pp (9.5pp)	-2.3pp (9.8pp)	-11.1pp (4.9pp)	-14pp (2pp)	-13.2pp (1.3pp)	-15pp (12.7pp)

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 for the median GCM values in parentheses are the standard deviation across all 17 GCMs. All results use the SSP-2 growth rates for baseline growth.

Figure A4: The direct welfare value of amenities: climate shocks during 2015–2100.



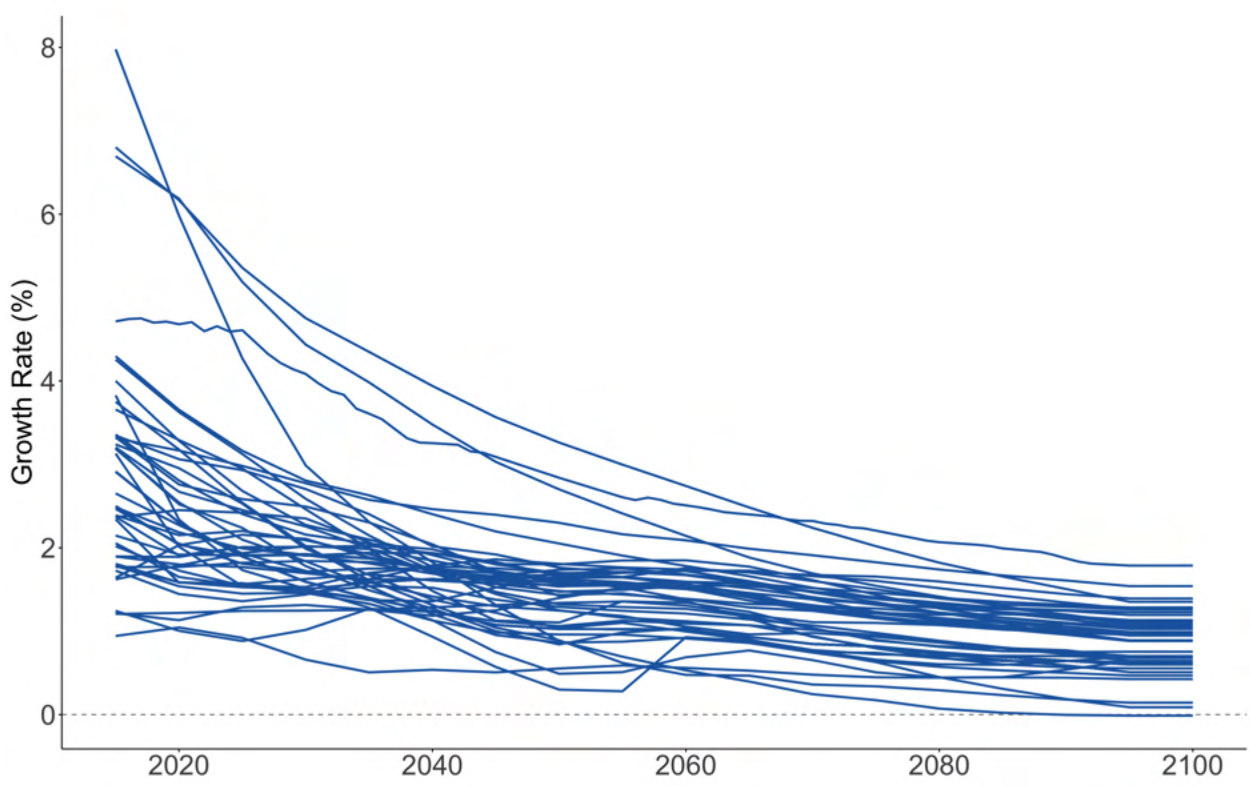
Note: The values on the map plot the direct climate impacts on amenities from equation (24). The map corresponds to our full model. The results for the median amenity welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

F.2 Population and Employment Trends

Figures A6 and A7 plot the time series of the change in population and employment shares due to climate change. The figures plot the effects under three scenarios: our full model in solid blue, the model with a homogeneous response function across industries in the red dashed line, and the model where trade does not adjust in response to climate change in dotted black.

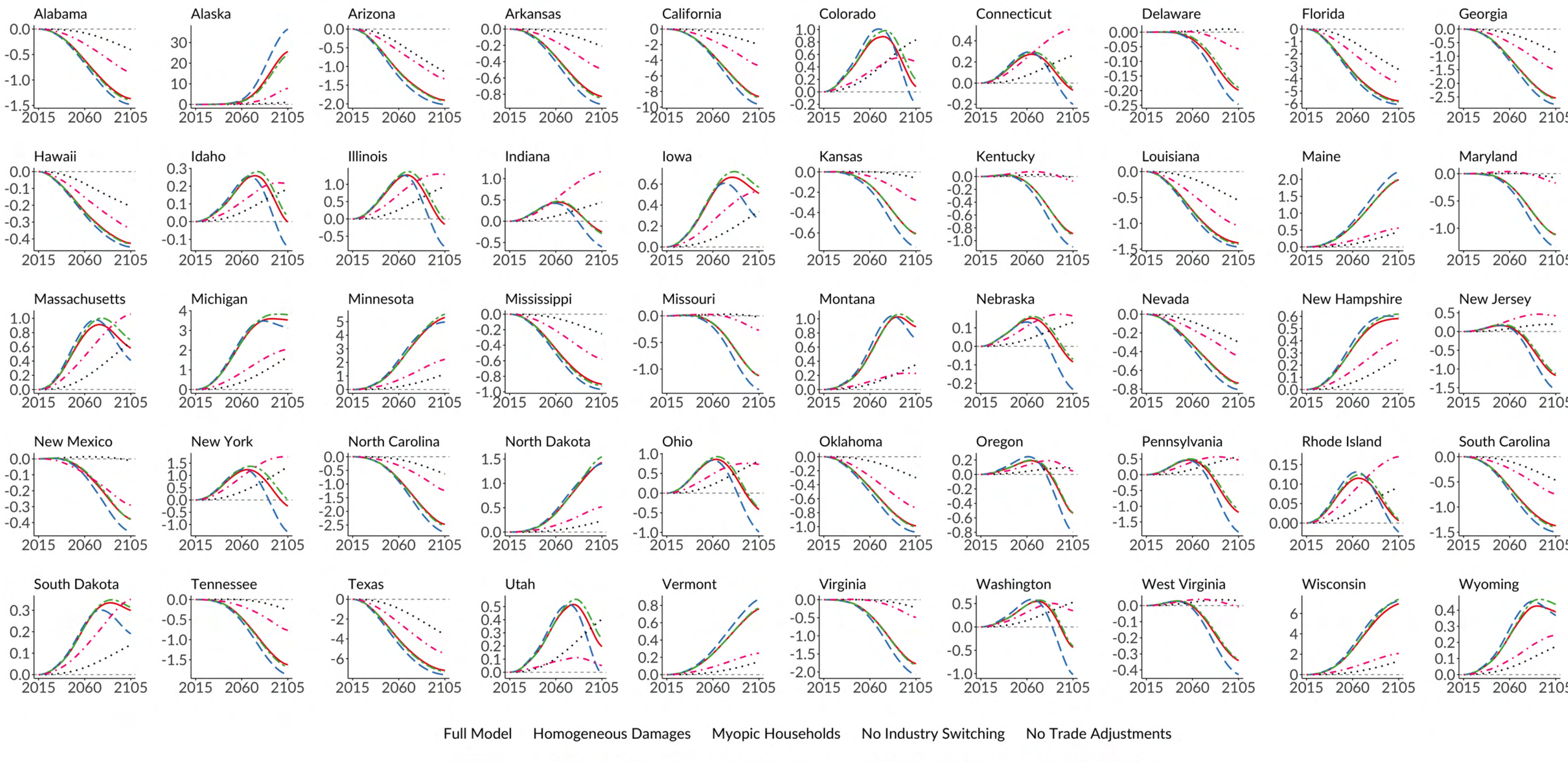
A few common themes can be seen in the graphs. First is that homogeneous damages tends to amplify migration out of southern states and into northern states. Second, heterogeneous damages and trade significantly amplify job switching: changes in industry employment in response to climate change are attenuated for almost all industries when response functions are homogeneous or trade cannot adjust. Third, unlike migration patterns, the effect of climate change on industry employment can be very different depending on whether other adaptation margins are possible and the model attributes.

Figure A5: SSP-2 country-specific growth rates.



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

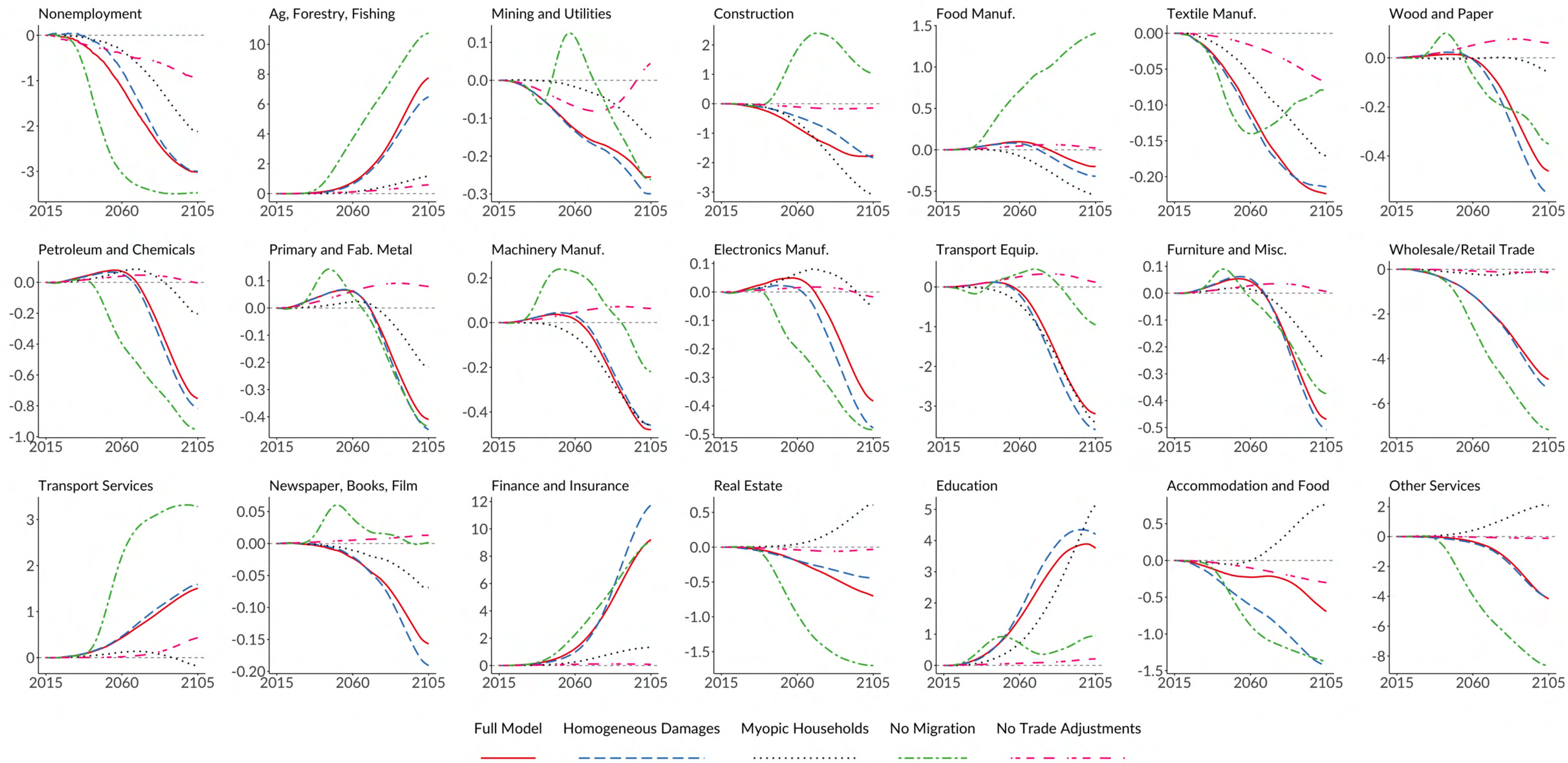
Figure A6: State population trends.



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. The counterfactual scenario is if the annual temperature distribution for each location was held constant at its 2015 level for 2015–2100. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals ($\dot{Z}_{i,t}^{k} = 1$ for all i, k) to allow the full impacts of the shocks to unfold. The solid blue line is for our full model, the red dashed line is for a model with a homogeneous response function across industries, and the black dotted line is for a model where trade cannot adjust to climate change. The results correspond to the median welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

A28

Figure A7: Industry employment trends.

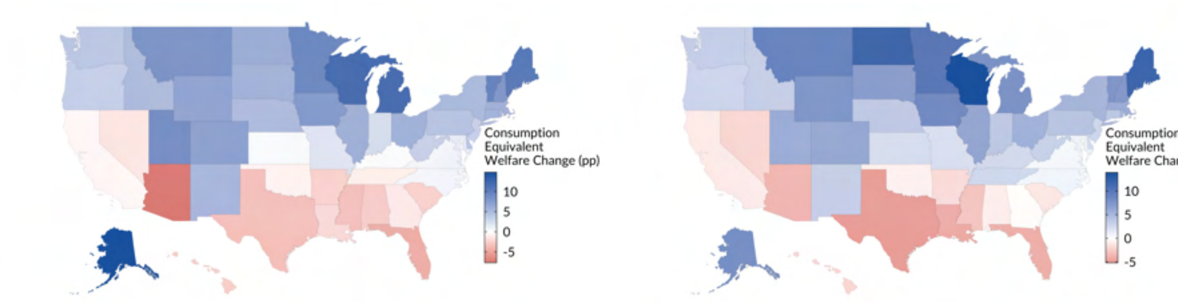


Note: The units are the percentage point changes in employment relative to no climate change counterfactual. The units are the fraction of total US population so total population sums to 1 and the total change sums to zero. The counterfactual scenario is if the annual temperature distribution for each location was held constant at its 2015 level for 2015–2100. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals ($\dot{Z}_{i,t}^{k} = 1$ for all i, k) to allow the full impacts of the shocks to unfold. The solid blue line is for our full model, the red dashed line is for a model with a homogeneous response function across industries, and the black dotted line is for a model where trade cannot adjust to climate change. The results correspond to the median welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

A29

Figure A8: Welfare value of adaptation mechanisms: 2015–2100.

Export Competition IO-Amplification of Export Competition



Note: The left panel is the pure export competition effect: the adaptation benefits of trade without input-output linkages. The right panel is how input-output linkages amplify the export competition effect: the difference between the top left panel of Figure 9 and the left panel here. The counterfactual scenario is if the annual temperature distribution for each location was held constant at its 2015 level for 2015–2100. Both the baseline and counterfactual are simulated for 2101–2200 with constant fundamentals ($\dot{Z}^k_{i,t} = 1$ for all i, k) to allow the full impacts of the shocks to unfold. All maps correspond to our full model with productivity shocks, amenity shocks, local structures, input-output loops, and heterogeneous response functions across industries. All maps show results for the median welfare outcome of the region across 17 RCP 4.5 GCMs and using the SSP-2 growth rates for baseline growth.

F.3 Trade Adaptation Decomposition

Figure A8 decomposes the effect of trade on welfare presented in Figure 9. The effect of trade can be decomposed into three pieces. First is what we call the pure export competition effect. This is how under trade, buyers substitute away from sellers in the South which further reduces welfare in the region. This is shown in the top left panel and is computed the same as the top left panel of Figure 9, but without input-output linkages. The two maps are similar except here the magnitudes are smaller.

The reason the magnitudes are smaller is because input-output linkages amplify this export competition effect: producers make similar substitution pattern changes as consumers. This almost always amplifies the magnitude of the export competition effect as shown in the right panel and 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 9 and the left panel of Figure A8.