The Food Problem and the Aggregate Productivity Consequences of Climate Change

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Abstract

Climate change is projected to sharply reduce agricultural productivity in hot developing countries and raise it in temperate regions. Reallocation of labor across sectors could temper the aggregate impacts of these changes if hotter regions shift toward importing food and specializing in manufacturing or exacerbate them if subsistence food requirements push labor toward agriculture where its productivity suffers most. I quantify these effects in two steps. First, I project changes in global comparative advantage by using firm-level micro-data from 17 countries covering over half the world's population to estimate the heterogeneous effect of temperature on output per worker in manufacturing and services. I find large effects of extremely hot and cold temperatures on non-agricultural output per worker, but treatment effects diminish with income and expectations of temperature such that the projected impact of climate change is larger in agriculture than non-agriculture. Second, I embed my estimates in an open-economy model of structural transformation that matches moments on output-per-worker, sectoral specialization, and trade for 158 countries. Simulations suggest that subsistence food requirements dominate labor reallocation in response to climate change on average and the global decline in GDP is 12.0% larger, and 52.1% larger for the poorest quartile of the world, when accounting for sectoral reallocation than in the counterfactual with fixed sectoral shares. The aggregate willingness-to-pay to avoid climate change is 1.5-2.7% of annual GDP and 6.2-10.0% for the poorest quartile. Trade reduces the welfare costs of climate change relative to autarky by only 7.4% under existing policy, but by 30.7% overall and by 68.2% for the poorest quartile in an alternative scenario with reduced trade costs.

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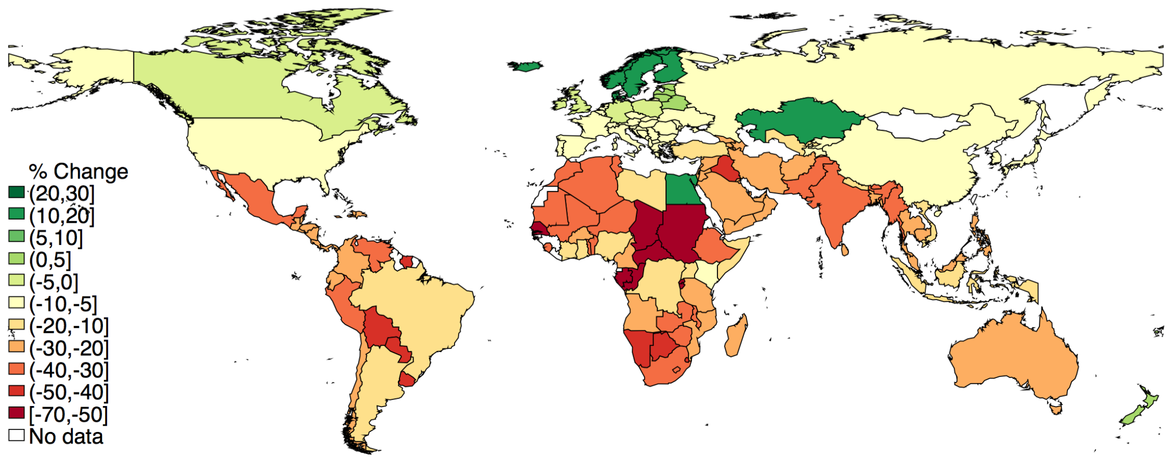
1 Introduction

Existing evidence suggests that climate change will cause large and heterogeneous changes in agricultural productivity across the world during the 21st century. Figure 1 shows estimates of the country-level impact of climate change on agricultural productivity from Cline (2007), which synthesizes evidence from economics, agronomy, and climate science.[1]

Figure 1: Cline (2007) Projected Impact of Climate Change on Agricultural Productivity, 2080-2099



Notes: Figure shows the projected change in revenue per acre from producing grains, vegetables, fruits, and livestock according to analysis by Cline (2007).

The projections in Figure 1 show large declines in agricultural productivity of 30-60% in hot regions such as Sub-Saharan Africa and South Asia, with neutral or positive effects in cold regions such as Canada and northern Europe. This pattern suggests large potential gains from shifting the geography of agricultural production. If productivity suffers greatly in some places and improves in others, perhaps market forces will temper the damage by pushing agriculture toward temperate climates while tropical regions reallocate production to other sectors? This paper investigates the conditions necessary for this hypothesis to hold true, and quantifies the aggregate productivity consequences of climate change in the presence of the changes in sectoral specialization likely to occur in practice.[2]

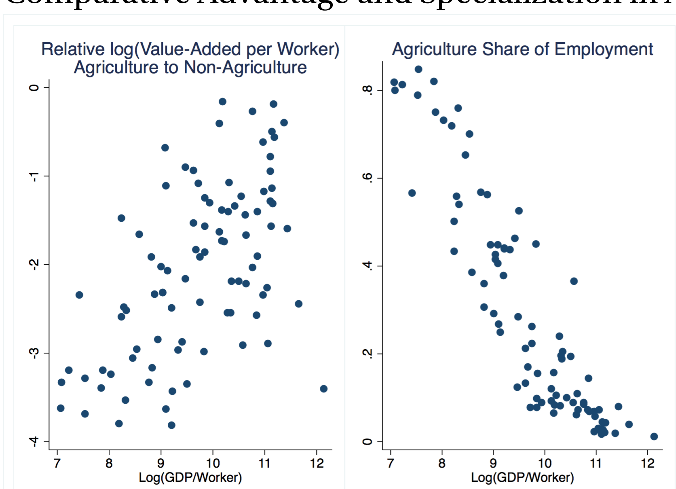
[1] I explain the methods used in Cline (2007) more in Section 7.1. The findings are broadly consistent with a large body of economics research on the impacts of climate change on agriculture, which includes Mendelsohn, Nordhaus and Shaw (1994), Deschenes and Greenstone (2007), Schlenker and Roberts (2009), and Schlenker and Lobell (2010), among many others. I use Cline (2007) in this paper because it is the best available source for country-level impact estimates that use globally representative data and account for adaptation.

[2] I use the phrase climate change to refer to shifting distributions of temperature in this paper. Other consequences of climate change, such as sea-level rise or intensified hurricanes, are beyond the scope of the analysis.

Two key elements of sectoral allocation complicate the idea that the changes in Figure 1 will push agriculture away from the equator. First, these estimates show the change in the absolute advantage of agricultural production, whereas comparative advantage across sectors drives international trade. Ricardian models of trade will only predict that Canada will export more food and India will import more food if the *relative* productivity of agriculture rises in Canada and falls in India.[3] Given existing evidence that temperature also affects non-agricultural productivity, the change in comparative advantage is not immediately clear.[4]

Second, comparative advantage does not exclusively, or even primarily, determine sectoral specialization. Figure 2 shows that poor countries have much higher agricultural labor shares despite lower relative value-added per worker in agriculture compared to non-agriculture. Lagakos and Waugh (2013) calculate that, adjusting for prices, the gap in aggregate output per worker between the 90th to 10th percentile of the world's income distribution is 45 to 1 in agriculture, but just 4 to 1 in non-agriculture. Yet agriculture's share of employment averages 65% in 10th percentile countries and only 3% in 90th percentile countries. Trade in agriculture plays only a small role in developing countries. The average person in the poorest quartile of the world consumes 91.3% domestically produced food, compared with 45.1% in the richest quartile. In these relatively closed economies, high agricultural production and labor shares follow from the high consumption shares necessary for people with low incomes to meet subsistence requirements for food. Projecting the effects of climate change on sectoral reallocation requires accounting for the

Figure 2: Comparative Advantage and Specialization in Agriculture



Notes: Figure shows data from Tombe (2015) that adjusts for prices for the global cross-section in 2005. Poor countries specialize heavily in agriculture despite low productivity relative to other sectors.

[3]I use the word food interchangeably with agricultural production in this paper because subsistence requirements for food drive the key features of consumer preferences in my analysis.

[4]This evidence includes work by Zhang, Deschenes, Meng and Zhang (2018) and Somanathan, Somanathan, Sudarshan, Tewari et al. (2015).

forces driving this existing global equilibrium in which poor countries specialize in agriculture despite low absolute and relative productivity, a fact which the literature on the general equilibrium effects of climate change has not yet confronted.

I address both these challenges in my analysis. First, to project changes in agricultural comparative advantage, I provide the first global micro estimates of the impact of climate change on productivity in manufacturing and services using a dataset of nationally representative firm-level panel data from 17 countries covering over half the world's population, and representing nearly the full range of current temperatures and income levels. Using methods developed by Carleton et al. (2018), I use my data to estimate plausibly causal treatment effects of extreme temperatures on output-per-worker, and account for firm-level adaptation by allowing these treatment effects to vary with income and expectations of temperature.

I find that extreme heat and extreme cold can both have important effects on non-agricultural productivity, but with strong evidence of adaptation in rich countries and to temperatures with which agents are accustomed. In poor countries with moderate climates, an extreme day with daily maximum temperature of 40°C or -5°C reduces annual output-per-worker by up to 0.4%, approximately the equivalent of one full working day.[5] Effects are about half as large in middle-income countries, and smaller still in those places that experience given extremes more frequently. The effects of extreme days in rich countries are negligible, with some evidence of mild effects from unexpected extremes caused by hot days in cold places and cold days in hot places. I combine these estimates of predicted temperature sensitivity with global climate model predictions of future temperatures to project the country-level effects of climate change on manufacturing and services productivity. The effects of climate change on non-agricultural productivity are non-trivial in some poor countries, but generally small relative to productivity losses in agriculture. Thus, the change in the global relative productivity in agriculture is qualitatively similar to the change in absolute productivity.

Second, I construct a global open economy model of structural transformation that explains the existing distribution of sectoral specialization as a function of sector-level productivities. The model incorporates two key features of consumer preferences - nonhomothetic preferences and low substitutability across sectors - that explain the high agricultural share of consumption in poor countries with high relative prices for food. Gollin, Parente and Rogerson (2007) refer to the macro-development effects of these subsistence requirements as "the food problem," which drives developing countries to specialize in a relatively low-productivity sector because people need food to survive. My model also includes Ricardian comparative advantage within and across sectors, which tends to force countries with low relative productivity in agriculture toward specializing production in other sectors, but only to the extent that they are open to trade.[6]

[5]I find similar effects for manufacturing and services firms, though I lack data coverage for services firms in poor countries where the effects of temperature are most detectable.

[6]While rural-urban migration within countries plays a key implicit role in the sectoral

Thus, my model shows that two competing effects govern the response of sectoral specialization to climate change, and that their net effect could either temper or exacerbate the aggregate consequences of the sector-level changes. If the trade effect dominates, then countries can dampen the effect of falling agricultural productivity by shifting production to other sectors; exporting more manufactured goods and importing more food. To the extent that climate change exacerbates 'the food problem' by reducing agricultural productivity, however, the general equilibrium response could drive labor toward the sector suffering large declines in productivity and worsen the aggregate impact.

To quantify the relative strengths of these mechanisms, I estimate my model to match data on income levels, trade flows, and sectoral specialization for 158 countries covering over 99.9% of global GDP. I embed the empirically estimated projected impacts of climate change on productivity in agriculture, manufacturing, and services into the estimated model, and conduct counterfactual simulations that calculate the effects of climate change on sectoral specialization, trade, prices, GDP, and welfare.[7] I disentangle the effects of 'the food problem' and trade by running separate counterfactuals with no reallocation, in autarky, with estimated trade costs, and in an alternative policy scenario with reduced barriers to trade.

I find that the net effect of sectoral reallocation exacerbates the effects of climate change on aggregate productivity. Climate change raises the agriculture share of GDP by 2.8 percentage points in the poorest quartile of the world, which suffers large falls in relative agricultural productivity, as 'the food problem' outweighs the trade response on average. Comparative advantage predominantly shifts away from the equator and net exports in agriculture increase in colder countries, such as those in northern Europe, and in a few hot countries that suffer declines in agricultural productivity that are small relative to those of their close trading partners or to their decline in manufacturing productivity. Net imports of food rise in most hot countries in the developing world, but only some countries are sufficiently open to trade for this effect to substantially alter sectoral specialization. Overall, climate change reduces global GDP by 12.0% more, and by 52.1% more for the poorest quartile of the world, when accounting for the full effects of sectoral reallocation than in the naive counterfactual with fixed sectoral shares.

The equivalent variation willingness-to-pay (WTP) to avoid each year of climate

reallocation captured by my model, I hold the global distribution of population fixed across countries rather than allowing for international migration. To justify this assumption, I note that some combination of home-bias and barriers to migration are sufficient to maintain welfare differences of two orders of magnitude between the poorest and richest countries in the existing global equilibrium. While climate change is likely to exacerbate global income differences, it seems plausible that the strength of these forces will continue to keep most people confined to the places where they already live. To the extent that climate change does cause substantial international migration, my analysis captures the welfare consequences for those people left behind in the countries suffering major impacts.

[7]My simulations use Cline (2007) for the effects of climate change on agriculture, and my own estimates for manufacturing and services.

change is between 1.5% and 2.7% of contemporaneous global GDP, depending on assumptions about economic growth. The worst effects are concentrated in poor countries that comprise a small share of global GDP, but a substantial portion of the population. The average person in the poorest quartile of the global income distribution suffers losses of 6.2%-10.0% of their income. Trade reduces the aggregate global willingness-to-pay to avoid climate change by 7.4% relative to autarky under existing policy, and by 30.7% under the alternative low trade barrier counterfactual. Reducing trade barriers has heterogeneous effects, increasing the costs of climate change in some regions as greater interdependence makes countries less vulnerable to local shocks but more vulnerable to global shocks.[8] Reducing trade barriers is particularly valuable for climate change adaptation in poor countries. Trade reduces WTP for the poorest quartile of the global population by only 4.5% relative to autarky under existing policy, largely because many poor countries are mostly closed to trade, but by 68.2% in the low trade cost counterfactual.

This paper relates to several literatures on climate change and macroeconomic development. The two most similar papers are Costinot, Donaldson and Smith (2016), who examine reallocation across crops but do not consider income effects or cross-sector reallocation, and Desmet and Rossi-Hansberg (2015), who primarily focus on the important role for international migration in climate change adaptation. The latter paper includes changes in the global distribution of sectoral specialization in the model, but does not attempt to incorporate realistic trade costs or the importance of 'the food problem' in the analysis. My paper is the first to consider the effects of climate change on structural transformation.

My empirical work on temperature and productivity builds on country-level estimates produced by Somanathan, Somanathan, Sudarshan, Tewari et al. (2015) and Zhang, Deschenes, Meng and Zhang (2018) in India and China. The model builds on several papers that consider structural transformation in an open-economy setting, including Tombe (2015), Uy, Yi and Zhang (2013), and Teignier (2018). I also use a nonhomothetic CES specification for consumer preferences from Comin, Lashkari and Mestieri (2015). Finally, some of my counterfactual predictions about the role of trade and the spatial correlation of shocks relate to the work of Dingel, Meng and Hsiang (2019).

The paper is structured as follows. Sections 2, 3, and 4 describe the data, empirical strategy, and results for the estimation of the relationship between temperature and non-agricultural productivity. Section 5 lays out the model. Section 6 explains the model estimation and describes the model's success in fitting the data. Section 7 contains the counterfactual model simulations. Section 8 provides additional country-level panel regression evidence on the impact of agriculture-biased productivity shocks on sectoral reallocation. Section 9 discusses implications for policy and Section 10 concludes.

[8]Note that this nets out gains from trade that are unrelated to climate change adaptation. Thus, these results do not imply that these countries are worse off overall from reducing trade barriers.

2 Data

Firm Data

I assemble a globally representative panel of firm-level microdata to estimate the relationship between temperature and productivity in manufacturing and services. Table 1 lists the countries and years included in the dataset as well as the data source for each country. The data combines surveys administered by national governments with data acquired from the Amadeus database maintained by Bureau van Dijk (BVD). BVD is a private company owned by Moody's Analytics that collects and distributes firm-level financial information from around the world. They collect data both by acquiring administrative data directly from national business registers and by conducting their own surveys.

Table 1: Global Firm-Level Panel Microdata

Country	Data Source	Dataset	Years
Austria	Bureau Van Dijk	Amadeus	1995-2014
Belgium	Bureau Van Dijk	Amadeus	1995-2014
China	National Bureau of Statistics	Chinese Industrial Survey	2003-2012
Colombia	National Administrative Department of Statistics (DANE)	Annual Manufacturing Survey	1977-1991
Finland	Bureau Van Dijk	Amadeus	1995-2014
France	Bureau Van Dijk	Amadeus	1995-2014
Germany	Bureau Van Dijk	Amadeus	1995-2014
Greece	Bureau Van Dijk	Amadeus	1995-2014
India	Central Statistical Office	Annual Survey of Industries	1985-2007
Indonesia	Badan Pusat Statistik	Annual Manufacturing Survey	1975-1995
Italy	Bureau Van Dijk	Amadeus	1995-2014
Norway	Bureau Van Dijk	Amadeus	1995-2014
Spain	Bureau Van Dijk	Amadeus	1995-2014
Sweden	Bureau Van Dijk	Amadeus	1995-2014
Switzerland	Bureau Van Dijk	Amadeus	1995-2014
United Kingdom	Bureau Van Dijk	Amadeus	1995-2014
United States	Census Bureau	Annual Survey of Manufacturers, Census of Manufacturers	1976-2014

Notes: Data includes revenue and number of employees, with varying coverage of capital stock (tangible fixed assets) and wage-bill. Amadeus data includes both manufacturing and services firms.

I restrict my analysis to those countries with nationally representative panels. This includes government-level surveys from India, Colombia, Indonesia, China, and the United States, and Amadeus data from twelve European countries with mandatory filing requirements according to BVD documentation.[9] Bloom, Draca and Van Reenen (2016) report that the data in most of these European countries contains nearly the full population of public and private firms.[10] Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez (2017) also use data from Amadeus and Alfaro and Chen (2018) use data from Orbis, a related firm dataset produced by BVD.

My sample covers both manufacturing and services firms in developed and developing countries. While the government surveys cover only manufacturing firms, the BVD data covers the entire spectrum of 2-digit industries. I report results for the pooled sample of all firms, separately for manufacturing firms, and separately for services firms, though the latter subset lacks developing country coverage.[11] BVD also reports additional branch locations and subsidiary ownership for many firms. I drop all firms that list subsidiaries or additional branches so that reported firm output aligns as closely as possible to my measure of temperature exposure at the main location. I also drop firms containing fewer than three observations and those with missing data for revenue or number of employees.

In total, the sample includes 17 countries that cover 59.4% of the world's manufacturing output and 51.1% of the global population.[12] The dataset also meets the globally representative criterion by spanning virtually the full range of climate and income levels in the global cross-section. According to the Penn World Tables, PPP-adjusted GDP per capita in my sample ranges from $1,137 in India in 1985 to $64,274 in Norway in 2014, which covers the 3rd to the 99th percentile of the global population in 2014. Similarly, country-level average daily maximum temperature in my sample ranges from 8.5 C°in Norway to 31.5 C°in India, covering the 1st to the 90th percentile of global population-weighted long-run temperature. Thus, to the extent that income and average temperature predict adaptation to extreme temperatures, my data is informative about the full range of heterogeneity in the global temperature-productivity relationship.

Climate Data

I use temperature data from Version 3 of the Global Meteorological Forcing Dataset (GMFD) produced at Princeton University. The data covers the entire world at a 0.25°by 0.25°grid for the years 1948-2016. GMFD is a reanalysis dataset that re-

[9]Importantly, the online version of the Amadeus database does not maintain accurate historical records. Thus, I download the data directly from the 2005, 2010, and 2015 vintages (CDs). Each Amadeus vintage contains 10 years of historical data for each firm. I match firms across years using BVD's unique firm identification number, and drop a small subset of observations with inconsistent data across vintages for the same firm-year.

[10]Denmark, Ireland, and Portugal also have mandatory reporting requirements, but were unavailable to me due to data licensing restrictions and missing or outdated geographic identifiers.

[11]I drop firms marked mining, construction, utilities, and agriculture, though results are very similar when including these firms in the pooled sample.

[12]I cannot include the United States in my main pooled specification because I can only access the data at a secure government facility. I also exclude the data from China from my main specification for data quality reasons explained in Section 4.

constructs historical temperature using a combination of observational data and local climate models. Following Graff Zivin and Neidell (2014) and other work on temperature and labor productivity, I use daily maximum temperature as my variable of interest to best approximate the temperature people experience during working hours.

I match firm and climate data at the county level. The government surveys provide county location for each firm directly. The BVD data provides city name and zip code, which I match to the county-level using GeoPostcodes, a global geocoding dataset provided by GeoData Limited.[13] I apply nonlinear transformations to the GMFD temperature variable at the pixel level, and then average across pixels to the county level weighting by population.[14]

Other Data

I use purchasing power parity adjusted GDP per capita data from the Penn World Tables as a measure of the income level of each country-year in my sample.

3 Empirical Strategy

In order to quantify the effects of climate change on sectoral reallocation and aggregate productivity, my empirical results must execute three objectives. First, I need to estimate the causal effect of temperature on productivity in manufacturing and services. Second, I need to estimate the heterogeneity in that relationship such that I can predict the response to temperature for every country in the world. The model counterfactuals in Section 7 require an estimate of the response of manufacturing productivity to temperature in Algeria without having data from Algeria. Third, my estimates should incorporate the benefits and costs of adaptation. Future projections should reflect the fact that the effects of a given temperature realization will likely diminish as countries grow richer, firms improve technology, and agents adjust expectations to the shifting distribution of temperatures. To quantify the effects of climate change in Section 7, I need to make projections not just for Algeria today, but for future Algerian firms experiencing climate change in 2080.

3.1 Conceptual Framework

To motivate my estimation strategy I start with a version of the production function from Burnside, Eichenbaum and Rebelo (1993) with variable labor effort:

$$Y = AK^{\alpha}(e * L)^{1-\alpha} \text{ with } 0 \leq e \leq 1 \tag{1}$$

[13]GeoData Limited estimates that their latitude and longitude coordinates for the center of each zip code are precise to within 100 meters. I independently verify a subset of observations in each country to ensure accuracy. I also hand-code a small number (under 1%) of unmerged observations using city name, and drop those unmerged observations for which the city name is non-unique within a country.

[14]For some countries, the administrative unit to which I aggregate is more comparable to a town than a county.

The parameter e governs effective units of labor input. Intuitively, temperature could affect e through several channels. Extreme temperatures could cause illness or physical fatigue, impair cognitive function, or increase the disutility of labor such that workers reduce effort or minutes spent working.[15]

Rearranging the production function in terms of output per worker and taking logs gives:

$$ln\left(\frac{Y}{L}\right) = ln(e) + \left(\frac{1}{1-\alpha}\right)ln(A) + \left(\frac{\alpha}{1-\alpha}\right)ln\left(\frac{K}{Y}\right) \tag{2}$$

Equation 2 provides the basis for using output per worker as the dependent variable in my main specification. The change in output per worker equals the change in e when the firm's technology and capital-to-output ratio stay constant.[16] To gain further insight into the firm's optimal response to climate conditions, I model worker effort as a function of exposure to extreme heat (cooling degree days), extreme cold (heating degree days), and adaptation investments b_h and b_c:[17]

$$\begin{gathered} e^* = 1 - CDD * g_h(b_h) - HDD * g_c(b_c) \\ g \geq 0, g' < 0, g'' > 0 \end{gathered} \tag{3}$$

In this framework, the firm has access to separate technologies that mitigate the impact of extreme heat and extreme cold on worker effort with diminishing returns in each.[18] The first order conditions for a profit-maximizing firm yield the following expression for the firm's optimal investment in hot weather adaptation b_h:

$$-g'(b_h) = \frac{c_h * e}{p * MPL * L * CDD} \tag{4}$$

Since g is convex in b_h, Equation 4 predicts that firm adaptation investments will be increasing in the firm's exposure to extreme heat (CDD), the marginal product of labor, the firm's labor input, and the price of output, and decreasing in the cost of

[15]The health effects of extreme temperatures have been widely documented, including in Deschênes and Greenstone (2011). Several laboratory experiments, including Seppanen, Fisk and Lei (2006) find evidence of reduced worker cognitive functioning. Graff Zivin and Neidell (2014) use time-use survey to show that people allocate less time to working in the presence of extreme temperatures.

[16]If capital is not adjustable in the short-run then short-run changes in $\frac{Y}{L}$ will slightly understate the change in e as $\frac{K}{Y}$ will also increase due to the fall in Y. In the long-run when the firm readjusts capital to its optimal level, the change in output per worker exactly equals the change in e.

[17]I define cooling degree days and heating degree days in Equation 6.

[18]Zhang, Deschenes, Meng and Zhang (2018) mention that capital equipment could also perform poorly in extreme temperature conditions. If so, augmenting the production function with variable effective capital utilization, u, as in Burnside and Eichenbaum (1996), would capture this effect. In that case, the interpretation in Equation 2 would be that the reduction in $\frac{Y}{L}$ was attributable to a combination of declines in e and u.

the adaptive technology, c_h, and the level of worker effort.[19] Thus, the firm's optimal condition predicts that worker effort will be less sensitive to temperature at more productive firms with more expected exposure to extreme temperatures, but that this reduced sensitivity comes at a cost.

To capture this heterogeneity, my empirical strategy focuses on modeling output per worker, and consequently e, as a function of temperature realizations, access to technology, and expectations over the distribution of temperature. By measuring the effects of climate change on e, I can use my estimates to project the change in the sector-by-country aggregate productivity parameters, Z_{jk}, that govern average output per worker in the model introduced in Section 5.

3.2 Causal Effect of Temperature

Following the framework outlined in Deryugina and Hsiang (2014), I start by noting that workers experience daily realizations of weather. San Francisco and Washington D.C. have similar annual temperatures, but very different exposure to extremes. To capture this logic, I treat daily output as a function of temperature on day d, $Y_d = f(T_d)$. To aggregate to annual output, the level of my data, I sum daily outputs along with functions of daily temperature, $f(T_d)$, across all days experienced by firm i in year t:

$$Y_{it} = \sum_{d=1}^{365} Y_{id} = \sum_{d=1}^{365} f(T_{id}) = F(T)_{it} \tag{5}$$

Thus, I treat nonlinear transformations of daily temperature summed over the year as my primary independent variable of interest. Using annual data also has the important advantage of allowing for intertemporal substitution of labor. If workers produce less due to extreme temperatures on Tuesday but produce extra on Saturday instead, annual data captures the effects of temperature net of this reallocation.

For parsimony, my main specification uses a piecewise linear functional form for temperature, where output is allowed to vary linearly with daily maximum temperature above 30°C (CDD) and below 5°C (HDD):

$$f(T) = \begin{cases} \beta_1(5 - T_{max}) & \text{if } T_{max} < 5 \\ 0 & \text{if } 0 \le T_{max} \le 30 \\ \beta_2(T_{max} - 30) & \text{if } T_{max} > 30 \end{cases} \tag{6}$$

This formulation allows cold and hot temperatures to have separately estimated effects, β_1 and β_2, on productivity. I also conduct robustness checks with more flexible functional forms such as a polynomial of degree four and bins of daily

[19] Optimal adaptation investment is decreasing in the level of worker effort because there are concave returns to effort.

maximum temperature.

Following other work in the climate impacts literature, I isolate the causal impact of temperature by exploiting interannual variation in weather. In line with the framework outlined in Section 3.1 my main specification models log output per worker at firm i in year t as a function of the vector of temperature effects, $\boldsymbol{\beta}$:

$$ln\left(\frac{Y_{it}}{L_{it}}\right) = \boldsymbol{\beta} F(T)_{it} + \delta_i + \kappa_{rt} + \epsilon_{it} \tag{7}$$

I control for permanent firm-specific features such as technology and management with firm fixed effects δ_i and for unobserved aggregate shocks such as technological progress and recessions with region (country or state) by year fixed effects κ_{rt}. I cluster my standard errors at the firm and county-by-year level to account for both serial and spatial correlation. Equation 7 allows for estimating the average treatment effect of temperature realizations, which fulfills part of the purpose of this section.

3.3 Heterogeneity and Adaptation

Following the strategy of Carleton et al. (2018), I allow for heterogeneity in the effect of temperature on output per worker by interacting the vector of temperature coefficients with income and long-run average temperature. This setup follows from the prediction in 3.1 that more productive firms in high-income countries and those that expect to experience extremes more frequently will be better adapted. I specify the interacted regression as follows:

$$\begin{aligned} ln\left(\frac{Y_{it}}{L_{it}}\right) = {} & \boldsymbol{\beta} F(T)_{it} + \boldsymbol{\gamma_1} ln(GDPpc)_{rt} \times F(T)_{it} \\ & + \boldsymbol{\gamma_2} TMEAN_i \times F(T)_{it} + \delta_i + \kappa_{rt} + \epsilon_{it} \end{aligned} \tag{8}$$

The interaction variables in Equation 8 are country-level annual GDP per capita and long-run average daily maximum temperature in the county containing firm i.[20]

Estimating Equation 8 allows me to predict the treatment effects of extreme cold, β_1, and extreme heat, β_2, as a function of two factors - income and average climate. While there are certainly other variables that affect temperature sensitivity, this parsimonious specification makes it feasible to predict the treatment effects in any country for which I have data on GDP per capita and average temperature. Given the existence of this data for the full range of countries in the global cross-section, as well as of readily available plausible future projections of temperature change and economic growth, this approach allows me to project the effects of

[20] I use country-level income because reliable data on subnational income is difficult to acquire. Average temperature is calculated as a 40-year average in the county of firm i, which is the same geographic scale at which contemporaneous temperature is measured.

temperature both across space and over time. In line with the goals for this section, the interacted model allows me to predict the effects of temperature in Algeria today and in Algeria in 2080.

The coefficients on the interaction terms in Equation 8 are identified using cross-sectional, rather than panel, variation, but the identification assumption is also weaker. Estimating the main causal effect of temperature relies on the standard identification assumption - that the independent variable of interest is uncorrelated with omitted variables that affect output per worker conditional on the set of controls. For the interaction variables, however, I am interested in how income and climate *predict* temperature sensitivity, rather than in isolating their specific causal effect. Thus, the identification assumption is not that income and climate are uncorrelated with omitted variables affecting temperature sensitivity, but rather that this correlation remains constant across space and over time. Indeed, the aim is to use income and average climate as a proxy for the full suite of underlying mechanisms, and omitted variables, that govern adaptation. The cross-sectional approach will produce valid predictions if the effects of temperature realizations on output per worker in parts of the world with income levels and average temperatures similar to India are similar to the effects measured in India.[21]

Allowing the treatment effects of temperature to vary with long-run conditions also bridges the gap between weather and climate. A primary concern with using weather variation to inform estimates of the costs of climate change is that the estimated treatment effects may change as agents adjust their expectations in the long-run. I address this concern by explicitly modeling the treatment effects as a function of those expectations, as represented by long-run average temperature. In my formulation, climate is a distribution of temperatures and weather is a draw from that distribution. By allowing the treatment effect of a draw to depend on the distribution, my estimates for the effects of each draw remain valid as the distribution shifts. Intuitively, a hot day in Toronto could be more harmful than a hot day in Texas because it is more unexpected, but becomes less so as Toronto warms and its agents adapt. I capture this effect by assigning Toronto the estimated treatment effect of Texas once it has heated up to that long-run temperature in the future.

4 Empirical Results

4.1 Main Regression Results

Table 2 contains the main results from estimating Equations 7 and 8. Column 1 displays the treatment effect of extreme temperatures for the average unit of output in the countries in my sample by weighting observations by country-level GDP and the inverse of each country dataset's sample size. While the estimated average treatment effects show that the effects of temperature are statistically different

[21]Empirical estimation of adaptation in the climate impacts literature broadly relies heavily on cross-sectional variation because of the inherent difficulty in finding quasi-experimental variation in long-run conditions.

from zero, the magnitude of these coefficients is far too small to be economically significant. The estimates in Column 1 imply that a day with maximum temperature of either -5°C or 40°C would reduce annual output per worker by just 0.03% relative to a day in the moderate range of 5°C to 30°C.

Table 2: Effects of Daily Temperature on Annual Revenue per Worker

	(1) Revenue/Worker	(2) Revenue/Worker	(3) Revenue	(4) Employment	(5) Revenue/Worker
TMax-30	-0.0000311	-0.00119	-0.00250	-0.00131	-0.00100
	(-2.29)	(-4.73)	(-6.80)	(-5.25)	(-4.03)
5-TMax	-0.0000315	-0.000956	-0.00180	-0.000842	-0.000452
	(-2.15)	(-2.15)	(-2.91)	(-1.92)	(-2.07)
(TMax-30) X log(GDPpc)		0.0000715	0.000178	0.000107	0.0000595
		(4.07)	(6.79)	(6.06)	(3.65)
(TMax-30) X $\overline{\text{TMax}}$		0.0000186	0.0000334	0.0000148	0.0000160
		(4.85)	(6.24)	(3.93)	(3.96)
(5-TMax) X log(GDPpc)		0.0000898	0.000167	0.0000769	0.0000416
		(2.14)	(2.85)	(1.85)	(2.02)
(5-TMax) X $\overline{\text{TMax}}$		-0.00000292	0.00000212	0.00000504	0.000000703
		(-1.54)	(0.93)	(2.85)	(0.59)
N	4125776	4125776	4125776	4125776	17938084
Manufacturing	X	X	X	X	X
Services					X
Firm FE	X	X	X	X	X
Country X Year FE	X	X	X	X	X
Inverse Sample Size Weights	X				
GDP Weights	X				
Countries Included	15	15	15	15	15

Notes: t-statistics in parentheses. Dependent variables all in logs. Standard errors are two-way clustered at the firm and county-by-year level. Column 1 shows the coefficients from estimating Equation 7 and Columns 2-5 show the results from Equation 8. Outcome variables come from the data sources listed in Table 1 and temperature data is from GMFD. Countries included are Austria, Belgium, Colombia, Finland, France, Germany, Greece, India, Indonesia, Italy, Norway, Spain, Sweden, Switzerland, and the United Kingdom. Section 4.3 shows results for the United States and Appendix C shows results for China.

Column 2 in Table 2 shows substantial heterogeneity in the effects of temperature on annual output per worker. Consistent with the approach taken in Carleton et al. (2018), I do not weight the regressions in which I model heterogeneity explicitly because the aim is to understand how the treatment effect varies across the full observed range of the interaction variables. The unweighted regression with differential sample sizes in different places also effectively allows areas with more data, and consequently more precise estimates of the effect of temperature, to contribute more to estimating the interaction terms.

The main effects of temperature in the unweighted interacted regression in Column 2 are large, negative, and precisely estimated, though the magnitudes cannot be interpreted without considering the interaction terms. The coefficients on both interaction terms for log GDP per capita are large and positive, indicating that richer countries are insulated from the effects of both extreme heat and cold. Consistent with intuition about adaptation to long-run conditions, the coefficient on the interaction term for average long run temperature is positive for hot extremes and negative for cold extremes, indicating that places are less susceptible to temperatures which they experience more frequently. All four interaction coefficients on income and average temperature are consistent with the predictions from Equation 4 - more productive firms with more exposure to given extremes invest more in adaptation.

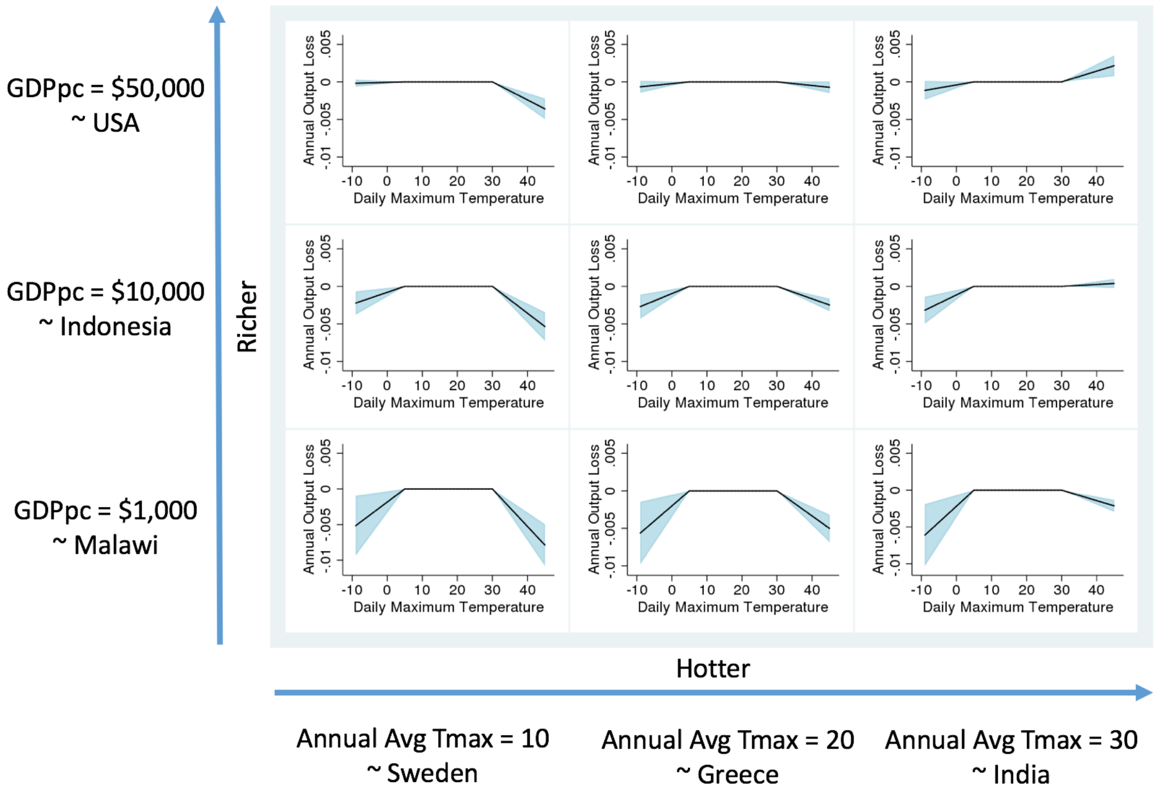
Figure 3 shows the predicted effects of temperature from Column 2 of Table 2 at points across the distribution of observed income and climate levels in the world. Consistent with the results of the GDP-weighted regression in Column 1, the graphs show that temperature has little effect on productivity in rich countries (top row), with some effects from hot days in cold, rich places (top left cell) and mild effects from cold days in hot, rich places (top right cell).

Conversely, extreme temperatures have very large effects on productivity in poor countries (bottom row). Experiencing one day at -5°C or 40°C in a poor country with moderate long-run temperatures (bottom middle cell) reduces annual output per worker by about 0.4%. In a working year consisting of 50 work weeks of 5 days each, this is equivalent to each worker reducing production on that day to zero with no compensating substitution to other days. These effects in poor countries imply potentially large productivity costs from climate change in hot parts of the world in the absence of adaptation. In parts of Sub-Saharan Africa, climate change projections imply an increase in extreme heat on the order of moving 100 days per year from 30°C to 40°C by 2080, which would suggest substantial declines in manufacturing productivity in poor countries.

Columns 3 and 4 of Table 2 separately estimate the effects of temperature on revenue and employment. The effects of both hot days and cold days on revenue are substantially larger than those on revenue per worker because firms adjust employment in response to extreme temperatures. As shown in Appendix Figures A-1 and A-2, which again evaluate the predicted coefficients throughout the covariate space, these effects also primarily manifest only in poor countries. This finding is consistent with the firm's first order condition in the framework laid out in Section 3.1 - firms should be expected to reduce labor input in response to the fall in the marginal product of labor driven by a decline in e. However, it is perhaps surprising that firms in my sample do not face adjustment costs large enough to dissuade this adjustment in response to the short-run variation used to identify these effects.

Column 5 of Table 2 shows the effects of temperature on a pooled sample of

Figure 3: Predicted Heterogeneous Response of Annual Manufacturing Revenue per Worker to Daily Maximum Temperature



Notes: Figure shows the predicted effect of temperature on revenue per worker at varying levels of income and long-run average temperature by evaluating the interacted regression from Column 2 of Table 2.

manufacturing and services firms. The effects are very similar to the sample of only manufacturing firms in both magnitude and patterns of adaptation, with the exception of the finding that colder countries are less vulnerable to extremely cold temperatures. The sample size increases substantially in this specification because many of the firms in my data are services firms, though I do not have any services coverage in low-income countries.

4.2 Robustness

I conduct robustness checks with different ways to specify the functional forms of temperature. Appendix Figures A-3 and A-4 show the predicted effects from the main specification in Column 2 of Table 2 using bins and a polynomial of degree four in daily maximum temperature, respectively. The results are qualitatively very similar to the main specification.

I also show robustness to including more stringent state-by-year, rather than country-by-year, fixed effects. The results are very similar for specifications that use all the data (pooling manufacturing and services firms) with more flexible functional forms such as bins or a polynomial of degree four. These two specifications are shown in Appendix Figures A-6 and A-7. These results are sensitive to functional form, however. The more parsimonious functional forms with a single parameter each governing the response to cold days and hot days show muted effects, particularly in the specification with manufacturing firms only. This is consistent with the fact that considerably less variation in temperature realizations remains within states in a given year, so more data and flexible estimation is necessary to recover the underlying pattern.

Figure A-8 shows robustness to including controls for capital. While the standard errors for this specification are somewhat larger because I lack data on capital for approximately a quarter of the observations in the main specification, the pattern of predicted effects is very similar.

4.3 U.S. Results

In this section, I use separate estimates of the effect of extreme temperatures on manufacturing in the United States to externally validate the results in Section 4.1.[22] Predictions using the global interacted regression suggest that temperature has a negligible effect on annual manufacturing revenues in rich, temperate countries such as the U.S. (see the top middle cell of Figure 3). Figure 4 shows the treatment effect of temperature on annual manufacturing revenue per worker estimated on data from the U.S. Census Bureau:

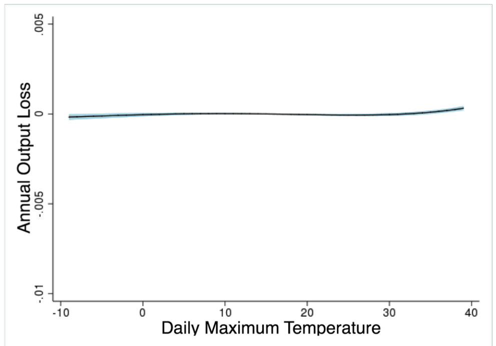
Consistent with predictions from global data in Figure 3, I find a precisely estimated null effect of temperature on output-per-worker in the U.S.[23] The U.S. data also includes information on other inputs that I lack in my global sample, allowing me to directly observe some of the adaptation costs incurred by U.S. firms. Appendix Figure A-13 shows that the average U.S. plant increases expenditures on electricity and other fuels by several thousand dollars for each extremely hot and cold day, presumably for cooling and heating expenses.[24] These expenditures are small in the context of U.S. plant size, however, such that temperature still has a null effect on revenue total factor productivity, which accounts for expenditures on energy and materials, as shown in Figure A-12.

[22]The results in Section 4.1 do not include data from the United States due to physical constraints on data access. Plant-level manufacturing data from the United States Census Bureau must be analyzed at restricted access Federal Statistical Research Data Centers (RDC).

[23]The result displayed in Figure 4 uses a polynomial of degree four in daily maximum temperature, but the null result is robust to choice of functional form. Appendix Table A-1 shows a range of specifications, all of which are consistent with a null effect on output and employment.

[24]Total energy expenditures are defined as the sum of electricity expenditures and the cost of other fuels. Full results for this outcome variable are shown in Appendix Table A-2.

Figure 4: Estimated Response of U.S. Annual Manufacturing Revenue per Worker to Daily Maximum Temperature



Notes: Figure shows the response of annual revenue per worker to a polynomial of degree four in daily maximum temperature estimated using Equation 7. Outcome variable data comes from the Annual Survey of Manufacturers and Census of Manufacturers from the U.S. Census Bureau. Temperature data is from GMFD. Standard errors are two-way clustered at the firm and county-by-year level.

4.4 Projected Global Sensitivity to Extreme Temperatures

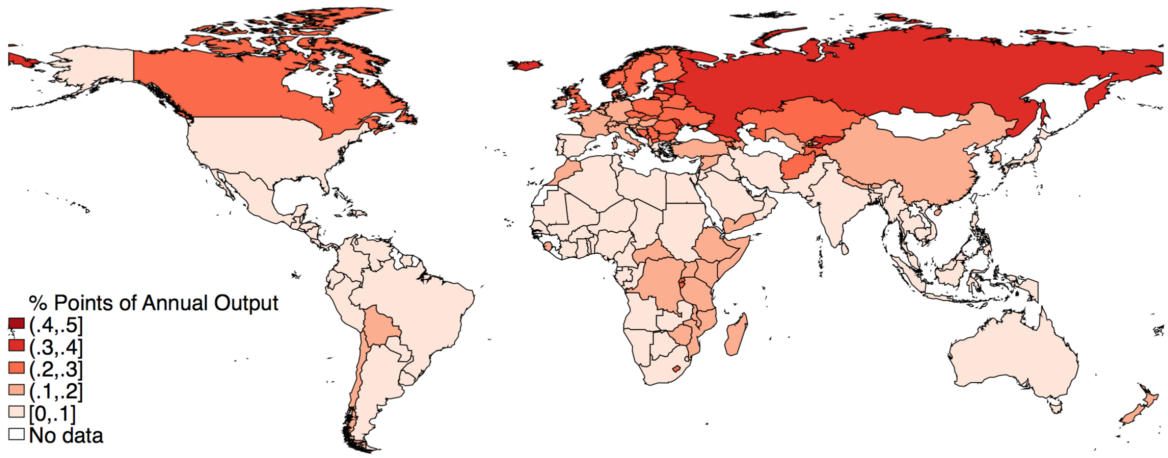
To connect the regression results from this section with the model presented in Section 5, I predict the effects of temperature in all 158 countries for which I will estimate the model. Figure 5 shows the predicted effects of a day with maximum temperature of 40°C on annual manufacturing revenue per worker and Figure 6 shows the effect of a -5°C day. Consistent with intuition about adaptation and the results displayed in Figure 3, poor countries and those which experience given temperatures less frequently are more susceptible to extreme realizations.[25]

Projecting the impacts of climate change also requires accounting for adaptation by adjusting the temperature sensitivities shown in Figures 5 and 6 to projected changes in long-run average temperature. The firm's optimal adaptation decision in Equation 4 implies that firms will increase investment in protection from extreme heat as the climate warms. I account for the benefits of these investments by reevaluating predicted heat sensitivity at projected end-of-century temperatures in Appendix Figure A-17.[26] The results show noticeably muted effects

[25]Note that following Carleton et al. (2018), these predictions define full adaptation as productivity that is invariant to temperature, and thus do not allow the effect of extreme temperatures to go above zero. The effects of extreme temperatures are weakly negative in the range of incomes and climates in the sample used for estimation, and I maintain this pattern as incomes and temperatures go out of sample.

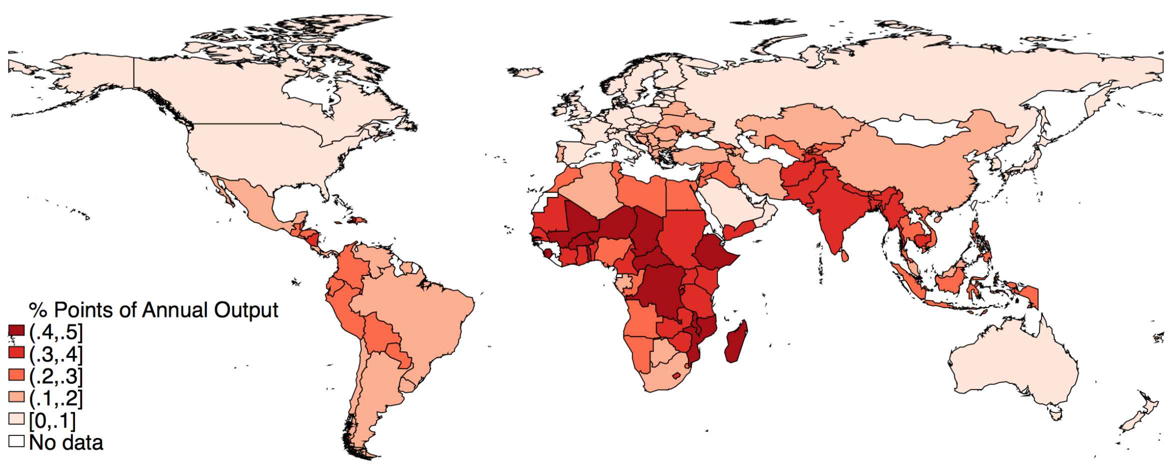
[26]End-of-century temperature projections are the 30-year average of annual average maximum temperature from the climate model predictions used in Section 7.1. In Section 7.6 I also allow for economic growth to make countries richer in the future, further reducing their temperature sensitivity.

Figure 5: Predicted Effect of a 40°C Day on Annual Manufacturing Revenue per Worker



Notes: Map shows the predicted annual percentage point loss in revenue per worker from a 40°C day obtained by evaluating the interaction regression in Column 2 of Table 2 at each country's level of income and long-run average temperature.

Figure 6: Predicted Effect of a -5°C Day on Annual Manufacturing Revenue per Worker



Notes: Map shows the predicted annual percentage point loss in revenue per worker from a -5°C day obtained by evaluating the interaction regression in Column 2 of Table 2 at each country's level of income and long-run average temperature.

when allowing for expectations to adjust to future temperatures. The mean global damage from a 40°C day is about 34% lower when evaluated at future temperatures (0.067% of annual revenues versus 0.1%) and firms in 67 countries become invariant to hot days compared with 39 countries at current temperatures.

The adaptation benefits of adjusting to extreme heat come at a cost. If it were costless to protect production from extreme heat, no firms would show effects of temperature on productivity. Instead, my results show that firms which experience given extremes infrequently find it optimal to invest less in adaptation, implying that the costs they would incur to achieve a marginal reduction in temperature sensitivity exceed the benefits. I leverage this intuition combined with the firm's first order conditions in Section 3.1 to infer a revealed preference measure of these adaptation costs following methods developed in Carleton et al. (2018). Appendix D covers the details of this calculation.

Quantifying the aggregate productivity consequences of climate change also requires projecting temperature sensitivity in services. I make projections for services using the pooled sample of manufacturing and services firms due to my lack of services data coverage in poor countries.[27] This choice follows from the estimated strong gradient of temperature sensitivity with respect to income but very similar coefficients between the manufacturing only and manufacturing/services pooled specifications in Columns 2 and 5 of Table 2.[28] Intuitively, my results suggest that manufacturing firms in India are a better proxy for services firms in India than services firms in Germany would be. Appendix Figures A-20 and A-21 show predicted current global sensitivity to hot and cold days in services using results from the pooled regression. I follow the same procedure to account for future adaptation benefits and costs as in manufacturing.

Overall, the results in this section allow me to predict the sensitivity of non-agricultural firm output per worker to extreme temperatures in every country in the world in the present and future. I use these results to project the impact of climate change on global comparative advantage between agriculture and manufacturing in Section 7.1, and to simulate the corresponding changes in sectoral allocation and aggregate productivity.

5 Model

This section lays out a static general equilibrium model of global production, consumption, and trade in agriculture, manufacturing, and services to analyze how changes in sectoral productivity affect sectoral specialization, trade flows, aggregate productivity, and welfare. I show that the model makes ambiguous predic-

[27] I show prediction results for regressions using only services firms in Appendix Figures A-9, A-10, and A-11. The results for extreme heat with more flexible functional forms such as a fourth degree polynomial are qualitatively similar to those of the pooled manufacturing and services regression, but these specifications are sensitive to functional form. Furthermore, the predictions in poor countries are extrapolating far out of the sample, which only includes European firms in a narrow range of high income levels.

[28] A formal test shows that coefficients for manufacturing and services firms in the pooled regression have statistically indistinguishable responses to extreme heat and marginally significant evidence that services firms are less susceptible than manufacturing firms to extreme cold.

tions about how reductions in agricultural productivity affect the labor share of agriculture, and that openness to trade is a key determinant of the aggregate consequences of asymmetric sectoral productivity shocks.

The ingredients of the model are as follows:

5.1 Model Ingredients

Consumption Following the demand system specified in Comin, Lashkari and Mestieri (2015), consumers in each country gain utility from final goods in each of the three sectors - agriculture, manufacturing, and services - according to the following implicitly defined utility function:

$$\Omega_a^{\frac{1}{\sigma}} U^{\frac{\epsilon_a}{\sigma}} C_a^{\frac{\sigma-1}{\sigma}} + \Omega_m^{\frac{1}{\sigma}} U^{\frac{\epsilon_m}{\sigma}} C_m^{\frac{\sigma-1}{\sigma}} + \Omega_s^{\frac{1}{\sigma}} U^{\frac{\epsilon_s}{\sigma}} C_s^{\frac{\sigma-1}{\sigma}} = 1 \tag{9}$$

Here, $\{\epsilon_a, \epsilon_m, \epsilon_s\}$ are utility elasticities for each sector that allow for nonhomothetic preferences, $\{\Omega_a, \Omega_m, \Omega_s\}$ are fixed sectoral taste parameters, and σ is the cross-sector elasticity of substitution. I choose this nonhomothetic CES preference specification because it can closely match the observed pattern of smooth structural transformation out of agriculture.[29]

Households consume their full wage, w, which varies at the level of country k. The aggregate budget constraint, summed across the country-level population L_k, equates income to total expenditures across the three sectors:

$$P_{ak}C_{ak} + P_{mk}C_{mk} + P_{sk}C_{sk} = w_k L_k \tag{10}$$

Demand for the final good in sector j in country k is given by:

$$C_{jk} = \Omega_j \left(\frac{P_{jk}}{w_k}\right)^{-\sigma} U^{\epsilon_j} \tag{11}$$

Production

The final good in sector j in country k is a CES composite of intermediate varieties indexed by i:

$$Y_{jk} = \left(\int_0^1 y_{ijk}^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}} \tag{12}$$

Intermediate goods producers each receive a productivity draw, z_{ijk}, drawn from a Frechet distribution with sector-specific shape parameter θ_j and sector-country specific start value Z_{jk}. The production function for intermediate goods is linear in

[29] Nonhomothetic CES preferences improve model fit substantially compared to using generalized Stone-Geary preferences, another common specification used to represent nonhomotheticity in the structural transformation literature, particularly in middle income countries. I show robustness to using Stone-Geary preferences in Appendix G.

labor:[30]

$$y_{ijk} = z_{ijk} * l_{ijk} \tag{13}$$

$$z_{ijk} \sim F_{jk} \text{ where } F_{jk}(z_i) = exp(-Z_{jk} z^{-\theta})$$
$$\text{and } Z_{jk} = f(\mu_{jk}, T_{jk}, E(T_{jk})) \tag{14}$$

The sector-country specific aggregate productivity parameters, Z_{jk}, connect the model to my empirical results in Section 4. In particular, I allow Z_{jk} to be a function of temperature realizations, T_{jk}, expectations over temperature, $E(T_{jk})$, and a vector, μ_{jk}, of country-sector specific features such as technology, institutions, and human capital. In making future projections in Section 7, climate change enters the model by perturbing the vector of Z_{jk} with empirically estimated productivity impacts that vary at the country-sector level.

Trade

The trade portion of my model follows Eaton and Kortum (2002). When selling to foreign countries, intermediate goods producers face an iceberg trade cost, τ_{ijk}, that varies at the exporter-importer-sector level. So, intuitively, shipping food from Canada to Malawi incurs a different trade cost than shipping food from Malawi to Canada, and manufactured goods shipped between Canada and Malawi have two separate trade costs of their own. Services are nontradable.

Intermediate goods producers price at marginal cost. Since labor is the only input, the price of a domestically produced good in country k is given by $p_{ijk} = \frac{w_k}{z_{ijk}}$. When selling to foreign country n and incurring the cost of trade, the intermediate goods producer in country k prices as follows:

$$p_{ijk} = \frac{\tau_{jkn} w_k}{z_{ijk}} \tag{15}$$

This representation of trade incorporates Ricardian comparative advantage both within and across sectors. A producer's ability to sell competitively priced exports depends both on their productivity and on the domestic wage. Low productivity countries will have low wages in equilibrium, so their relatively productive producers will be able to export their products even if their absolute productivity is low. Thus, relative productivity between sectors is the key determinant of net imports and exports.

The final goods producer sources each variety from the lowest-priced producer. The sectoral final goods prices are given by the CES price index of all intermediate

[30] Excluding capital from the model is implicitly equivalent to assuming freely mobile and undistorted capital markets around the world. In future drafts, I plan to conduct a robustness check with land included as an input.

varieties used in that sector:

$$P_{jk} = \left(\int_0^1 p_{ijk}^{1-\eta} di \right)^{\frac{1}{1-\eta}} \tag{16}$$

Intuitively, the price of the final good in agriculture, P_{ak}, can be thought of as a price index for the complete basket of food items while the price of each individual variety, p_{iak}, is the price of one particular food, such as apples. η is the elasticity of substitution between varieties.

Equilibrium

The model has two equilibrium conditions. First, total income in country k is the sum of all domestic and foreign sales in all three sectors.

$$w_k L_k = \sum_{j=1}^{3} \left(\pi_{jkk} P_{jk} C_{jk} + \sum_{n \neq k}^{N} \pi_{jkn} P_{jn} C_{jn} \right) \tag{17}$$

Here, π_{jkn} is the share of varieties from sector j consumed in country n that country k produces. So country k receives income both from its production share of domestic consumption in sector j, and from the share of consumption in every foreign country comprised of its exports. Since consumption equals income in each country, this condition also ensures that trade balances.

The second equilibrium condition concerns the labor market. The total labor force is allocated across the three sectors:

$$L_k = L_{ka} + L_{km} + L_{ks} \tag{18}$$

In autarky, market-clearing requires that income equals expenditures in each sector, $P_{jk} C_{jk} = w_k L_{jk}$, which means that the labor share, l_{jk}, equals the expenditure share, X_{jk}. In the open-economy case, the labor share equals the production share of revenues in each sector, incorporating net exports. This gives the following equation from Uy, Yi and Zhang (2013):

$$l_{jk} = \pi_{jkk} X_{jk} + \sum_{n=1}^{N} \pi_{jkn} X_{jn} \frac{w_n L_n}{w_k L_k} \tag{19}$$

This condition illustrates the importance of both domestic consumer preferences and international trade in determining the sectoral allocation of labor. Intuitively, Equation 19 says that if country k has agricultural consumption worth 30% of spending and agricultural net exports worth 10% of GDP, then 40% of its labor force will be in agriculture.

Aggregate GDP Losses and Willingness-To-Pay

I calculate the willingness-to-pay to avoid climate change productivity impacts as equivalent variation using the nonhomothetic measure of utility from the Comin, Lashkari and Mestieri (2015) preference specification.

I also quantify the aggregate GDP effects of sectoral productivity changes by using a Törnqvist (1936) price index that uses sectoral expenditure shares from before and after the shock, (X_{jk0} and X_{jk1}), to construct an aggregate price index with which to deflate nominal income:

$$P_k^T = \prod P_{jk}^{(X_{jk0}+X_{jk1})/2} \longrightarrow GDP_k = \frac{w_k L_k}{P_k^T} \tag{20}$$

This captures the logic of Baqaee and Farhi (2017), who extend Hulten (1978) to show that the aggregate productivity impact of a sectoral shock is given by the weighted average of the pre and post-shock sectoral shares. The intuition here is simple. If productivity falls markedly in agriculture, the aggregate impact is accentuated if more of the economy moves into agriculture and tempered by reallocation to other sectors. Thus, quantifying the magnitude and direction of sectoral reallocation is a key part of estimating the aggregate productivity consequences of climate change.

5.2 Comparative Statics

I now use the model to characterize the factors that influence sectoral reallocation in response to climate change. Consider a country that suffers an agriculture-biased reduction in aggregate productivity, consistent with projections for hot parts of the world made in Section 7. To see how the labor share in agriculture changes in Equation 19, I first consider the impact on the agricultural expenditure share, X_{ak}. The expression for X_{ak} from solving the consumer's problem is as follows:

$$X_{ak} = \Omega_a \left(\frac{p_{ak}}{P_k}\right)^{1-\sigma} \left(\frac{w_k}{P_k}\right)^{\epsilon_a-(1-\sigma)} \tag{21}$$

Taking logs gives:

$$logX_{ak} = log(\Omega_a) + \underbrace{(1-\sigma)log\left(\frac{p_{ak}}{P_k}\right)}_{\text{Substitution Effect}} + \underbrace{(\epsilon_a-(1-\sigma))log\left(\frac{w_k}{P_k}\right)}_{\text{Income Effect}} \tag{22}$$

The agriculture-biased reduction in productivity has two effects that appear in Equation 22.[31] First, the reduction in productivity drives down the equilibrium real wage ($\frac{w_k}{P_k}$), making consumers poorer. If $(\epsilon_a - (1-\sigma)) < 0$, as is the case with the parameter estimates presented in Section 6, then the reduction in real wage drives up the expenditure share on food, X_{ak}. This is the effect of nonhomotheticity. Food

[31] This equation also appears in Comin, Lashkari and Mestieri (2015). They estimate that nonhomotheticities (the income effect) account for about 75% of observed historical structural transformation, with changes in relative prices (the substitution effect) accounting for the rest.

is a larger share of consumption for poorer people, so climate change tends to drive up the share of agricultural consumption by making people poorer.

Second, the relative decline in agricultural productivity will increase the domestic price of agricultural goods relative to the aggregate price index ($\frac{p_{ak}}{P_k}$).[32] If $\sigma < 1$, as is also the case in Section 6, then the rising relative price of agricultural goods raises the expenditure share on agriculture. Intuitively, if food is not substitutable with other consumption, then its relative quantity falls less than the relative price rises, and the share of spending on food goes up. This is the same logic that underlies Baumol's cost disease (Baumol and Bowen, 1966), a theory that endeavors to explain why low-substitutability service sectors with relatively low productivity growth, such as health care and education, tend to rise as a share of expenditures over time.

Together, nonhomotheticity and low substitutability at the sector level combine to push up the expenditure share on agriculture in response to declines in agricultural productivity. The macro-development literature on structural transformation (see, for instance, Gollin, Parente and Rogerson (2007)) refers to these features of consumer preferences as 'the food problem' - the explanation given to the large share of the labor force in agriculture in most developing countries despite very low absolute and relative productivity.

These features of the model also explain why my model's predictions about the protective effects of reallocation diverge from those of Costinot, Donaldson and Smith (2016). Their paper finds that reallocating production across crops reduces the aggregate damages from climate change by two-thirds. To capture reallocation at the crop level, their model has no income effects and high substitutability across products.[33] This specification makes sense for capturing reallocation across crops, but does not generalize to the cross-sector case where income effects become important and the elasticity of substitution is very low. Intuitively, if the productivity of corn falls markedly relative to the productivity of wheat, consumers can respond by eating more wheat. If the productivity of producing food falls relative to the productivity of manufacturing, however, consumers cannot subsist by eating more manufactured goods.

In contrast to the food problem, the Ricardian comparative advantage effects of falling relative productivity in agriculture will tend to push labor into other sectors. Returning to Equation 19, shifting comparative advantage away from agriculture will tend to push up food imports (π_{akk} falls for country k) and push down food exports (π_{akn} falls). Equation 23 captures the horserace between the food problem and international trade that drives general equilibrium sectoral reallocation in re-

[32] In a closed economy, relative sectoral prices are exactly proportional to sectoral productivities. In an open economy, the domestic relative price of agriculture responds to domestic agricultural productivity in proportion to the domestic share of consumption.

[33] They estimate an elasticity of substitution of 5.4 across varieties of the same crop and 2.82 across crops. I estimate an elasticity of 0.29 between sectors.

sponse to climate change.[34]

$$l_{ak} = \underbrace{\pi_{akk}}_{\downarrow}\underbrace{X_{ak}}_{\uparrow} + \underbrace{\sum_{n\neq k}^{N} \pi_{akn} X_{an} \frac{w_n L_n}{w_k L_k}}_{\downarrow} \tag{23}$$

In autarky, falling relative agricultural productivity would drive up the labor share in agriculture, exacerbating the aggregate productivity costs. In an economy with costless trade, climate change would dramatically shift the global geography of agricultural production and trade flows, substantially limiting the aggregate costs. To quantify the relative strength of these effects in practice, I need to estimate the parameters of the model and simulate the general equilibrium response to the estimated impacts of climate change on productivity at the country-sector level.

6 Model Estimation

6.1 Parameter Estimates

I estimate the model presented in Section 5 to match data from 158 countries on sectoral GDP shares, bilateral trade flows in agriculture and manufacturing, and value-added per worker. Table 3 shows a list of the target moments and data sources corresponding to each model parameter. For the trade data obtained from UN Comtrade, I classify HS 1988/92 codes 1-24 as agriculture and 28-97 as manufacturing to best approximate food and non-food imports.[35]

I estimate consumption parameters and trade costs using simulated method of moments.[36] To assign values to Z_{jk}, I choose country level relative sectoral productivities to match the ratio of value-added per worker in agriculture, manufacturing, and services, and adjust the overall level of $\{Z_{ak}, Z_{mk}, Z_{sk}\}$ to match country-level nominal GDP.[37] I calibrate the trade elasticities using the values estimated by

[34]The importance of trade for promoting structural transformation out of agriculture has been previously emphasized by Tombe (2015), Teignier (2018), and Uy, Yi and Zhang (2013).

[35]Since trade data is reported in gross output terms but GDP is in value-added, I deflate the trade data by country-sector-level value-added to output ratios obtained from the United Nations Statistical Division. Following recommendations from UN Comtrade documentation, I use importer-reported trade data where possible, but default to exporter-reported data for smaller developing countries with large discrepancies between importer and exporter reported data.

[36]To simulate the model, I directly draw productivities from the Frechet distributions for 20,000 varieties for each sector for each country. I assign the production of each variety in each country to the lowest cost producer based on wages, trade costs, and productivity. I then find the vector of wages under which the equilibrium condition holds and national income equals national spending for every country. I estimate the consumption parameters to match sectoral share data using the patternsearch algorithm in Matlab, and choose bilateral trade costs to match the data on bilateral trade flows by sector.

[37]Since trade flows are in nominal terms, I match nominal GDP in the model for consistency. The nonhomothetic price index deflates nominal income to a measure of welfare.

Table 3: Model Parameters and Target Moments

Parameters	Data Moment	Data Source
σ	Sectoral GDP Shares	World Bank
Ω_a, Ω_m, Ω_s	Sectoral GDP Shares	World Bank
ϵ_a, ϵ_m, ϵ_s	Sectoral GDP Shares	World Bank
θ_a, θ_m	Calibrated from Tombe (2015)	
τ_{jkn}	Trade Flows	UN Comtrade
Z_{jk}	Sectoral Value-Added per Worker	World Bank
L_k	Population	World Bank

Notes: Table shows the data sources for moments targeted in my simulated method of moments procedure to estimate parameters for the model presented in Section 5. Data is for the global cross-sectoin in 2011, accessed from the World Bank Databank.

Tombe (2015); $\theta_a = 4.06$, and $\theta_m = 4.63$.

Table 4 displays my estimates of the preference parameters for the nonhomothetic CES utility specification. Two points about these estimates are worth noting. First, I estimate a cross-sector elasticity of substitution, $\sigma = 0.27$, of substantially less than one, indicating that the expenditure share in a sector sharply increases with its relative price. My estimate of σ to target the global cross-section of sectoral shares matches up well with that of Comin, Lashkari and Mestieri (2015), who use various historical panel datasets to estimate σ between 0.2 and 0.6. Second, I estimate that $\epsilon_a - (1 - \sigma) = -0.44$, which implies from Equation 22 that the consumption share of agriculture is strongly diminishing in real income. Thus, my parameter estimates imply clearly that a decline in aggregate productivity concentrated in agriculture will raise the expenditure share of agriculture through both the income and substitution effect.

6.2 Model Fit

The model closely matches the features of the data most relevant to the counterfactual simulations of the impacts of climate change. Table 5 summarizes the correlation between key simulated moments in the model and their empirical counterparts.[38] I match the income level of each country almost exactly by scaling the country-level aggregate productivity parameters. Similarly, my simulations closely

[38]A coefficient of 1 with $R^2 = 1$ would constitute a perfect fit. The fit for other moments in the model is displayed in Appendix Figures A-27 to A-32.

Table 4: Parameter Estimates

Parameter	Description	Estimate
σ	Cross-Sector Elasticity of Substitution	0.27
ϵ_a	Agriculture Utility Elasticity	0.29
ϵ_m	Manufacturing Utility Elasticity	1
ϵ_s	Services Utility Elasticity	1.15
Ω_a	Agriculture Taste Parameter	11.73
Ω_m	Manufacturing Taste Parameter	3.70
Ω_s	Services Taste Parameter	10

Notes: Parameters estimated using simulated method of moments. Ω_s is normalized to 10 as only relative values of Ω_j affect consumer choices. Since the focus is on cross-sector reallocation, I set the elasticity of substitution across varieties, η, equal to 1 for tractability so that varieties have equal revenue shares.

match the domestic production share of agricultural consumption since I choose exporter-importer-sector-specific trade costs, τ_{jkn}, to match all observed bilateral trade flows.[39] As shown in Appendix Figure A-33, most developing countries import little of their food. In the data, the average person in the poorest quartile of the world consumes 91.3% domestically produced food (89.4% in the simulation) compared to 45.1% in the richest quartile (52.4% in the simulation). I present suggestive evidence on some of the underlying causes of these high barriers to trade in poor countries in Section 9.

My model also explains most of the variation in the global agriculture share of GDP. I slightly under-predict agricultural shares on average, but overall the model explains 60.3% of the variation in the data. This is a relatively strong fit considering that only the seven free parameters in Table 4 were chosen to match 316 independent target moments consisting of GDP shares for agriculture, manufacturing, and services in 158 countries. As shown in Figure 7, the nonhomothetic CES demand specification enables the simulation to closely mirror the smooth decline of agricultural GDP with log income per capita.[40]

The model also reproduces the general pattern of high relative prices for agricultural consumption in poor countries - a moment I do not target in my estination. In Figure 8, I compare the simulated pattern of the relative price of agri-

[39]The simulated domestic production shares of expenditures have no systematic bias, but explain only 81% of the variation in the data because some countries have imbalanced trade.

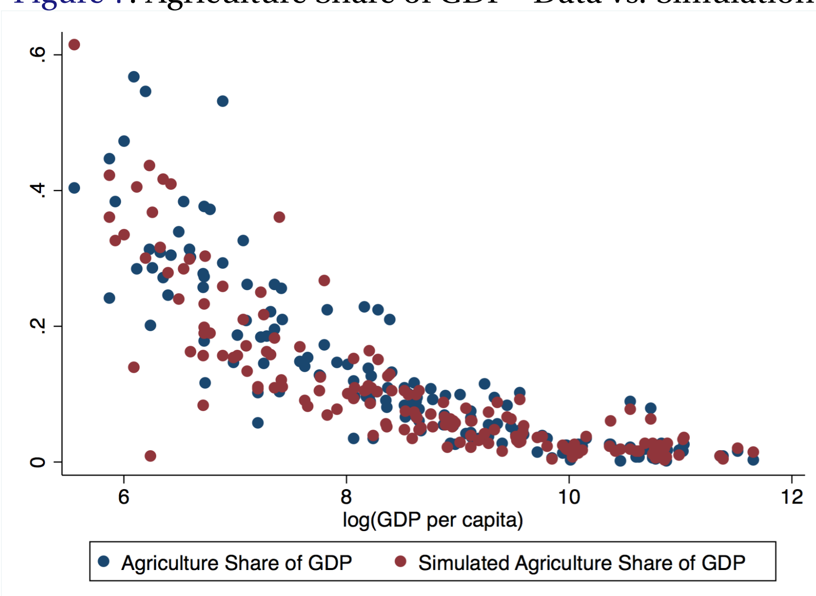
[40]For comparison, the best fit using a Stone-Geary utility specification has an R^2 of 0.43 and predominantly underpredicts the agriculture share as shown in Appendix Figure A-34.

Table 5: Summary of Model Fit

	(1) Data log(GDP per capita)	(2) Data Ag Share of GDP	(3) Data π_{akk} (Ag Domestic Production Share)
Simulated log(GDP per capita)	1.006		
	(0.00251)		
Simulated Ag Share of GDP		0.866	
		(0.0563)	
Simulated π_{akk}			1.009
(Ag Domestic Production Share)			(0.0392)
Observations	158	158	158
R^2	0.999	0.603	0.809

Notes: Table shows the results from regressing empirical moments in the data on their simulated counterparts. Data on nominal income levels and the agriculture share of GDP are from the World Bank. Data on the domestically produced share of expenditures in agriculture is constructed using Comtrade data.

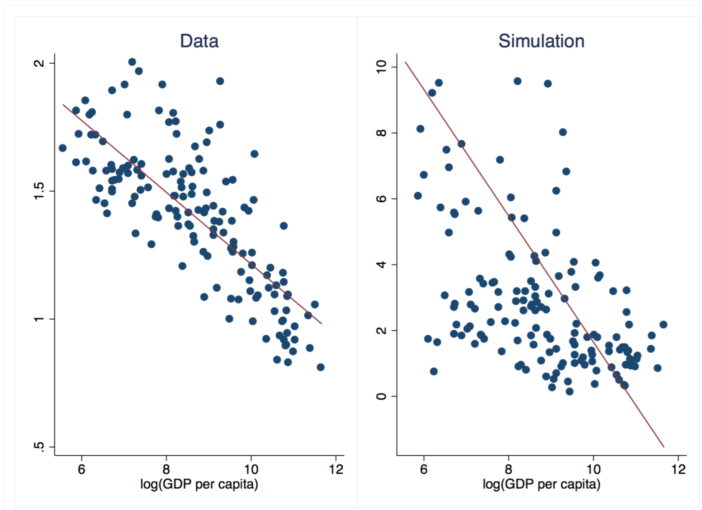
Figure 7: Agriculture Share of GDP - Data vs. Simulation



Notes: Graph shows the fit of simulated agriculture share of GDP in the model to data from the World Bank. The simulation explains over 60% of the variation in the data, and reproduces the smooth pattern of non-homotheticity observed in the empirical relationship between agriculture shares and income.

cultural and manufacturing consumption, P_{ak} and P_{mk}, to an empirical analogue constructed using aggregate sectoral price indices from the World Bank's International Comparison Program. While the simulated and empirical price indices have different units that prevent direct comparison, they share the same pattern of high relative prices for food in developing countries with low relative agricultural productivity.

Figure 8: Relative Price of Food - Data vs. Simulation



The graph on the left shows the ratio of a country-level food price index to an aggregate price index using data from the International Comparison Program. The graph on the right shows an analogous moment in the model - the ratio of the aggregate agricultural and manufacturing price indices, P_a and P_m. The model reproduces the empirical relationship that poor countries tend to have higher relative prices for food - a moment I do not target in my estimation.

Overall, the model matches the existing global pattern of sectoral specialization through a combination of consumer preferences and barriers to trade. Low incomes and the high relative price of food drive up agriculture's share of expenditures in poor countries through the nonhomotheticity and low elasticity of substitution in the preference specification. High estimated trade costs chosen to rationalize observed trade flows tightly link domestic consumption to domestic production, causing many developing countries to specialize in agriculture despite its low relative productivity.[41] In the next section, I use the model to investigate projected sectoral reallocation and its welfare consequences in response to climate change.

[41] As discussed in Section 5, this explanation is consistent with the work of Tombe (2015), Gollin, Parente and Rogerson (2007), and the broader literature on structural transformation.

7 Model Counterfactuals

This section uses the estimated model to project the impacts of climate change on trade flows, sectoral specialization, prices, GDP, and welfare.

7.1 Estimated Productivity Impacts

I start by projecting the impacts of climate change on country-sector level productivity. For agricultural productivity effects, I use the estimates from Cline (2007) displayed in Figure 1. This analysis uses micro-data from 18 countries in Africa, North and South America, and Asia representing over 35% of the world's agricultural production to estimate Ricardian cross-sectional regressions of agricultural output (in dollars) from grains, fruits, vegetables, and livestock as a function of temperature, precipitation, and irrigation. Because we expect farmers to have optimized crop choice and land use decisions in response to local long-run climate conditions, I interpret the estimated effects of temperature and precipitation from these cross-sectional regressions as net of adaptation through choice of crops and livestock. Projections using the empirical estimates are averaged with projections from leading crop models from agronomy, which also account for adaptation through crop-switching and adjusted farming techniques.[42] I use Cline (2007) in my analysis because it uses globally representative data to produce results broadly consistent with the literature on climate and agricultural production, and represents the most comprehensive available source of global impact estimates that account carefully for adaptation within the agricultural sector.

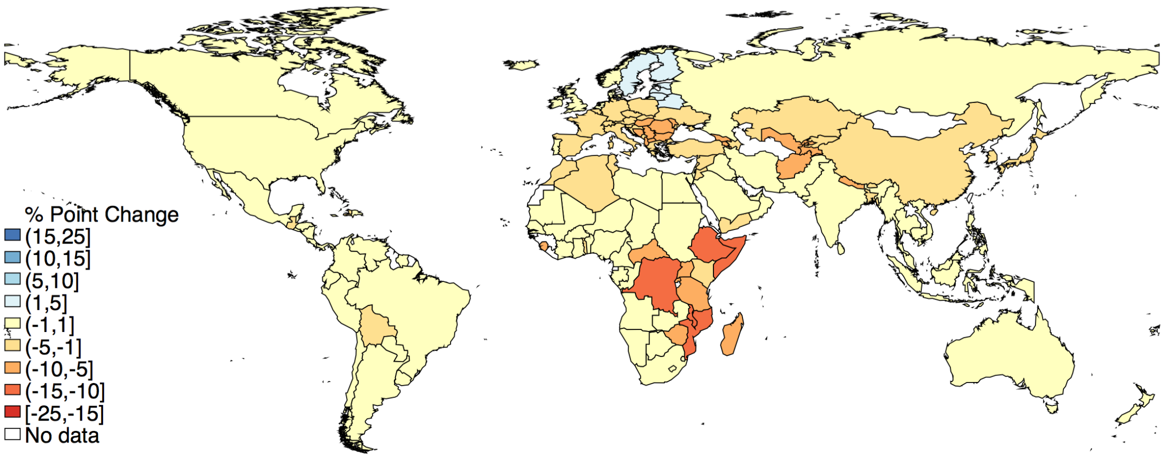
To project the impact of climate change on productivity in manufacturing and services, I combine the country-sector specific temperature sensitivities estimated in Section 4.4 with projections of the future distribution of temperature in 2080-2099.[43] I obtain future temperature predictions from the CSIRO-MK-3.6.0 model produced by Jeffrey et al. (2013), one of the climate models used by Cline (2007), for consistency with the projected changes in agricultural productivity.[44] The projected changes in manufacturing and services productivity are shown in Figure 9 and Appendix Figure A-24 respectively. Figure 10 brings together the estimated impacts on agricultural productivity from Cline (2007) with my estimates of the change in manufacturing productivity to show the change in the relative produc-

[42]The crop model projections in Cline (2007) account for reallocation across crop types within country, shifting planting dates, and increased irrigation and fertilizer use. None of the estimates in the analysis account for any response of international trade.

[43]I use the estimates that allow for firms to adjust adaptation investments to their end-of-century temperatures. I account for the costs of this adaptation in Section 7.6.

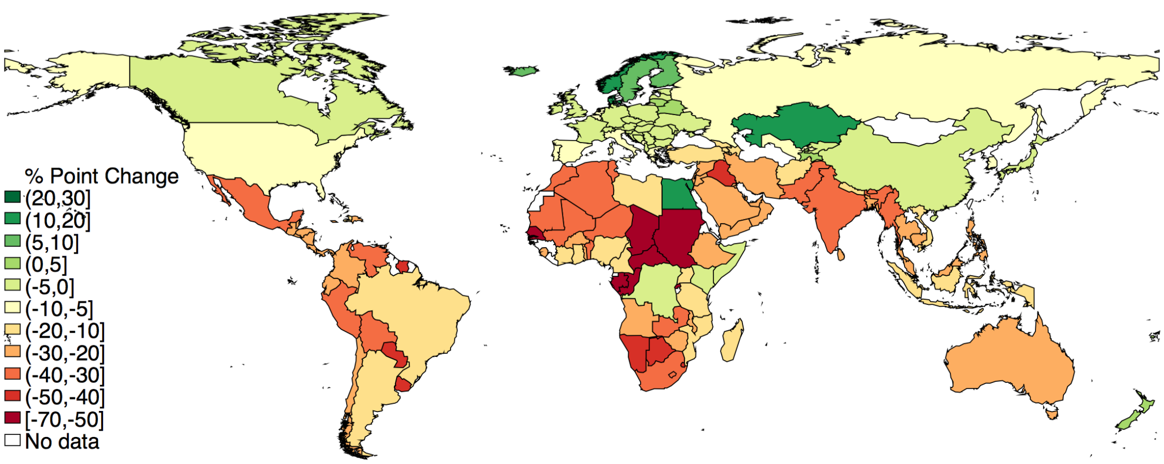
[44]My estimates from the interacted model in Section 4 give me an estimate of the reduction in annual manufacturing and services output per worker for each degree-day above 30°C and below 5°C. The CSIRO model projections give me population-weighted change in degree-days above 30°C and below 5°C for every country in the world in 2080-2099, which are shown in Appendix Figures A-22 and A-23. I multiply the country-level coefficients by the projected changes in hot and cold temperatures to get the impacts shown here.

Figure 9: Projected Impact of Climate Change on Manufacturing Productivity



Notes: Map shows the projected impact of climate change on manufacturing productivity in 2080-2099 obtained by multiplying predicted temperature sensitivities by CSIRO-MK-3.6.0 global climate model predictions of changes in exposure to extreme heat and cold. Temperature sensitivities are calculated by evaluating the interaction regression from Column 2 of Table 2 at each country's income and end-of-century long-run average temperature.

Figure 10: Projected Impact of Climate Change on Agricultural Relative Productivity



Notes: Map shows the change in agricultural productivity from Cline (2007) minus my estimate of the change in manufacturing productivity, shown above, in percentage points.

tivity of agriculture among the tradable sectors for each country in the world.

The pattern in Figure 10 shows clearly that climate change shifts comparative advantage in agriculture toward colder countries far from the equator on average.

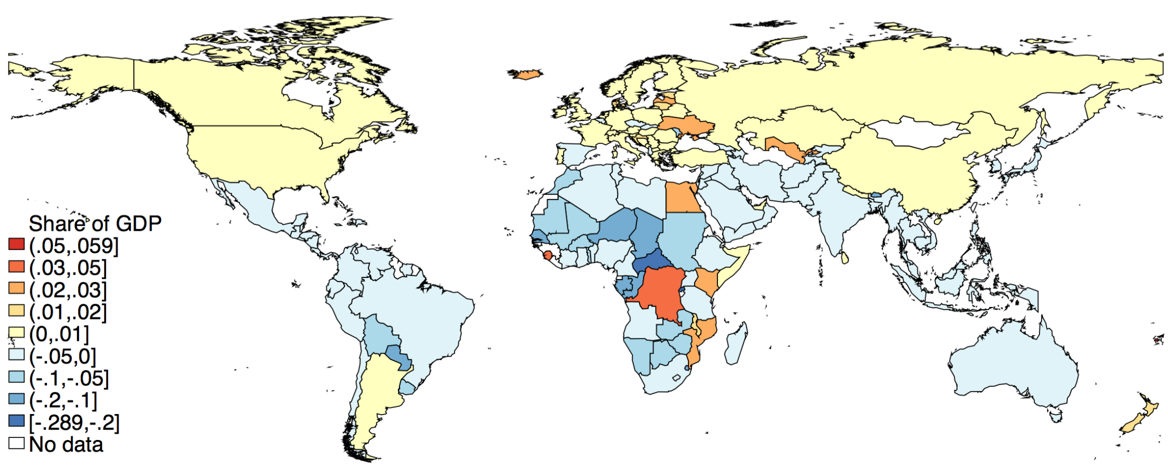
While the negative effects of climate change on manufacturing productivity are concentrated in similar parts of the world to agricultural productivity, they are generally smaller in magnitude. Every country in Africa, South Asia, and Latin America (with the exception of Egypt) has larger estimated productivity losses in agriculture than manufacturing. Thus, to the extent that specialization follows Ricardian comparative advantage, we would expect to see agricultural production move toward colder places away from the equator in response to climate change.

I integrate these empirically estimated into the model by applying them to the sector-country specific aggregate productivity Z_{jk} and recalculating equilibrium wages, prices, and trade flows.

7.2 Comparative Advantage and Trade

Figure 11 shows the projected equilibrium change in agricultural net exports in response to climate change. Consistent with the estimated change in comparative advantage, the predominant pattern is that hotter countries experiencing large declines in agricultural productivity import more food, while cooler countries with neutral or improving agricultural productivity export more food. For instance, Denmark and Canada roughly double agricultural net exports, from 1.9% to 3.8% and 0.5% to 1.2% of GDP respectively. Conversely, most of Sub-Saharan Africa and South Asia increase imports of food. The few exceptions to this finding are those hot countries for whom the change in agricultural productivity is not large relative to the change in manufacturing productivity, particularly in relation to their close trading partners.

Figure 11: Projected Impact of Climate Change on Agricultural Net Exports



Notes: Map shows model simulations of the change in agricultural net exports as a share of GDP driven by the effects of climate change on sector-level productivity and comparative advantage shown in Figure 10. The full set of country-level results shown in this map are listed in Appendix Tables A-3 to A-20.

The magnitudes of the projected change in trade flows are generally modest as a share of the economy. No country increases agricultural net exports by more than 6% of GDP, and only 12 out of 158 countries decrease agricultural net exports by more than 10% of GDP. The full set of country-level changes in net exports and the domestically produced share of agricultural consumption, (π_{akk}), are shown in Appendix Tables A-3 to A-20.

7.3 Sectoral Reallocation

As shown in Section 5.2, the change in trade flows is only a partial summary of the change in sectoral specialization. Agriculture's share of GDP (and consequently the labor force) depends on both the change in net exports and the change in the expenditure share on food. I reproduce Equation 23 summarizing labor reallocation in response to an agriculture-biased decline in productivity here for convenience:

$$l_{ak} = \underbrace{\pi_{akk}}_{\downarrow} \underbrace{X_{ak}}_{\uparrow} + \underbrace{\sum_{n=1}^{N} \pi_{akn} X_{an} \frac{w_n L_n}{w_k L_k}}_{\downarrow}$$

The change in net exports shown in Figure 11 captures the first and third effects in the above equation. Given the strong nonhomotheticity and low cross-sector elasticity implied by the estimates of ϵ_a and σ in Section 6, the change in the agriculture expenditure share, X_{ak}, is also likely to be substantial.

The horserace between these two competing effects - comparative advantage and 'the food problem' - that govern sectoral reallocation in response to climate change plays a critical role in the aggregate productivity and welfare consequences. As discussed in Section 5, the simple logic formalized by Baqaee and Farhi (2017) is that production moving toward the sector suffering a larger decline in productivity exacerbates the aggregate consequences of a given shock.

I decompose the competing effects of climate change on the agriculture share of GDP by running separate counterfactuals with and without trade. In autarky, the change in a sector's relative price equals the change in that sector's productivity. Thus, I start by applying country-sector level price changes equal to the inverse of the projected change in productivity and calculating the change in expenditure shares. This gives me the change in X_{ak}, which in autarky equals the change in agriculture's share of GDP. In contrast, the standard counterfactual incorporating trade gives me the full effect of both types of reallocation. Table 6 displays the baseline, autarky counterfactual, and trade-inclusive counterfactual agriculture shares of GDP for a selection of countries, and Appendix Tables A-21 to A-29 contain these results for all 158 countries.

The results in Table 6 show that the consumption response and trade response both have substantial effects on specialization in agriculture, with significant heterogeneity across countries. In Ethiopia, India, and Zambia, the 'food problem' ef-

Table 6: Counterfactual Ag GDP Shares - Selected Countries

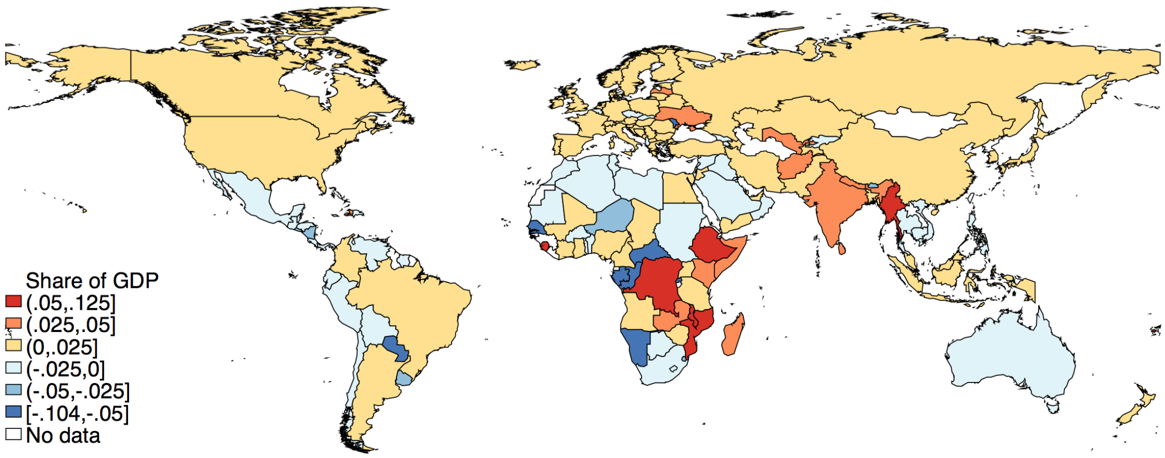
Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Argentina	-.111	0	.065	.067	.07
Brazil	-.169	0	.063	.071	.068
Canada	-.022	-.007	.019	.019	.026
China	-.072	-.036	.064	.068	.074
Denmark	.109	.006	.033	.032	.051
Ethiopia	-.313	-.102	.359	.437	.409
India	-.381	0	.161	.224	.194
Kenya	-.054	-.044	.156	.16	.185
Mozambique	-.217	-.104	.367	.426	.451
Rwanda	-.601	-.058	.409	.678	.351
United States	-.059	.003	.023	.024	.028
Zambia	-.396	0	.36	.496	.41
Poorest Quartile	-.319	-.02	.199	.256	.227
World	-.101	-.01	.038	.044	.043

Notes: Table shows model simulations of the change in agriculture share of GDP driven by the effects of climate change. The full set of country-level results shown in this map are listed in Appendix Tables A-21 to A-29.

fect dominates and the agriculture share of GDP rises in response to climate change despite large relative declines in agricultural productivity. In contrast, the trade effect dominates in Rwanda, where the domestic share of agricultural expenditures falls from 85% to 54%. Other countries, such as Canada, Denmark, and Kenya see an increase in agricultural specialization because of increased exports driven by improvements in relative agricultural productivity compared to their trading partners.

Figure 12 shows the full worldwide change in agriculture's share of GDP. On average, the global agriculture share of GDP rises from 3.8% to 4.3% because agricultural productivity falls in more places than it rises, raising X_{ak}, and net exports for the world are zero. More specifically, the 'food problem' effect particularly dominates on average in those countries suffering large relative declines in agricultural productivity. The average change in the agriculture share of GDP for countries facing a 10% or larger decline in relative agricultural productivity, weighting by their share of agricultural workers, is +2.1 percentage points from an initial share of 17.3%.

Figure 12: Projected Impact of Climate Change on Agricultural GDP Share



Notes: Map shows the model simulations of the change in the agriculture share of GDP driven by climate change. Appendix Tables A-21 to A-29 contain the full set of country-level results pictured here.

7.4 Aggregate Productivity and Willingness-to-Pay

The estimated sectoral productivity effects combined with the changes in sectoral specialization map directly into changes in aggregate productivity. Table 7 shows the change in real GDP for each counterfactual in select countries, deflating nominal income at the country level using the Tornqvist price index from Equation 20. The results for the full set of countries are shown in Appendix Tables A-30 to A-38.

The results make clear that projected reallocation *exacerbates* the impact of climate change on aggregate productivity in most countries, as well as globally on average. Global GDP declines 1.9% in the counterfactual that holds sectoral shares fixed, but 2.1% when allowing for reallocation. GDP in the poorest quartile of countries falls by 8.3% in the no reallocation counterfactual, and 12.6% with reallocation. This happens for two reasons. First, as discussed in Section 7.3, the 'food problem' pushes up the labor share of agriculture in many countries while agricultural productivity declines dramatically. Second, as Dingel, Meng and Hsiang (2019) have shown, the spatial correlation of the productivity impacts heighten their importance. Since food prices in Rwanda are a function of agricultural productivity in Rwanda and its closest trading partners, the losses to Rwanda intensify when accounting for the full general equilibrium effects, including those of shocks that hit their neighbors.

How can reallocation that worsens aggregate productivity and measured GDP be consistent with optimizing behavior? In Table 8, I calculate the willingness-to-pay (WTP) to avoid climate damages under each counterfactual as the equivalent variation loss in income at the baseline equilibrium set of wages and prices. The

Table 7: Counterfactual GDP Losses (Share of GDP) - Selected Countries

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Argentina	-.111	0	-.002	0	.001
Brazil	-.169	0	-.01	-.015	-.013
Canada	-.022	-.007	-.018	-.018	-.016
China	-.072	-.036	-.043	-.045	-.045
Denmark	.109	.006	0	0	.005
Ethiopia	-.313	-.102	-.163	-.218	-.217
India	-.381	0	-.074	-.131	-.127
Kenya	-.054	-.044	-.037	-.038	-.034
Mozambique	-.217	-.104	-.14	-.192	-.199
Rwanda	-.601	-.058	-.334	-.557	-.508
United States	-.059	.003	0	0	.001
Zambia	-.396	0	-.175	-.328	-.314
Poorest Quartile	-.319	-.02	-.083	-.132	-.126
World	-.101	-.01	-.019	-.023	-.021

Notes: Table shows model simulations of the change in GDP driven by the effects of climate change. The full set of country-level results are shown in Appendix Tables A-30 to A-38.

results show that the full reallocation counterfactual mitigates the welfare consequences of climate change, as captured by willingness-to-pay, even while increasing the impact on GDP. The WTP under the no reallocation counterfactual is particularly dramatic because it forces agents to deviate from optimal consumer behavior. This highlights that the no reallocation counterfactual is, in some sense, an unrealistic straw man. In the presence of very large projected increases in food prices, keeping fixed the expenditure share on food would require declines in the quantity of food consumed that are strongly inconsistent with the observed low substitutability between food and non-food. To summarize the intuition, people are willing to sacrifice income (GDP) to reallocate expenditures toward food when food prices rise because they need food to survive.

Figures 13 and 14 show the global distribution of willingness-to-pay to avoid climate change, and the change in food prices, P_{ak}, which comprise a key driver of the welfare losses. Food prices rise in 156 of the 158 countries, and rise by at least 25% in 41 countries containing over 32% of the world's population.[45] Climate change does net damage as measured by WTP in 150 countries, and causes welfare losses exceeding 8% of GDP in 32 countries covering 27% of the world's population.

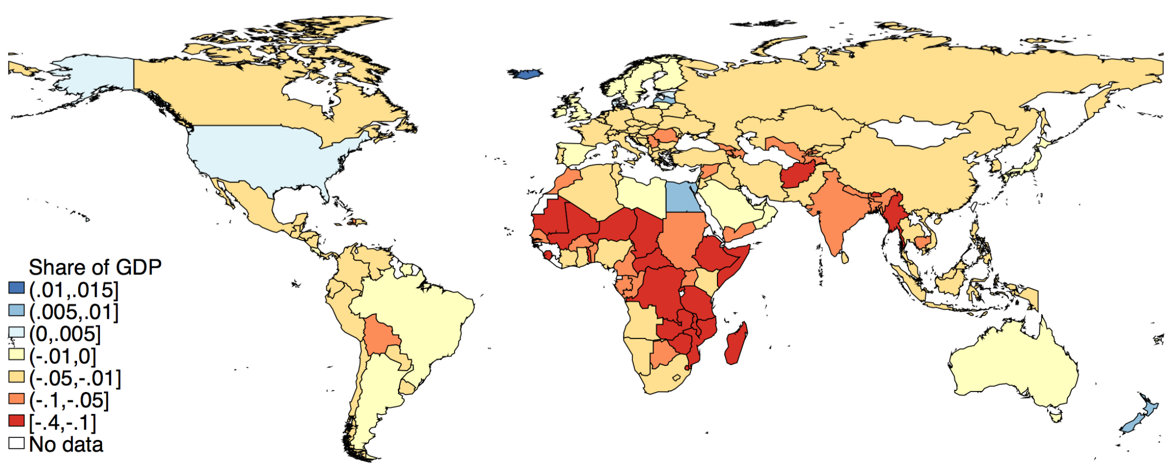
[45]The large changes in food prices also imply that the incidence of these losses may fall on urban consumers as much or even more than on farmers suffering lost productivity.

Table 8: Equivalent Variation Willingness-to-Pay (Share of GDP) - Selected Countries

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Argentina	-.111	0	-.008	-.002	0
Brazil	-.169	0	-.041	-.01	-.008
Canada	-.022	-.007	-.018	-.016	-.014
China	-.072	-.036	-.057	-.04	-.04
Denmark	.109	.006	.003	0	.005
Ethiopia	-.313	-.102	-.364	-.171	-.169
India	-.381	0	-.311	-.085	-.082
Kenya	-.054	-.044	-.052	-.035	-.031
Mozambique	-.217	-.104	-.279	-.143	-.147
Rwanda	-.601	-.058	-.725	-.434	-.387
United States	-.059	.003	-.002	0	.001
Zambia	-.396	0	-.481	-.208	-.199
Poorest Quartile	-.319	-.02	-.277	-.092	-.088
World	-.101	-.01	-.04	-.018	-.017

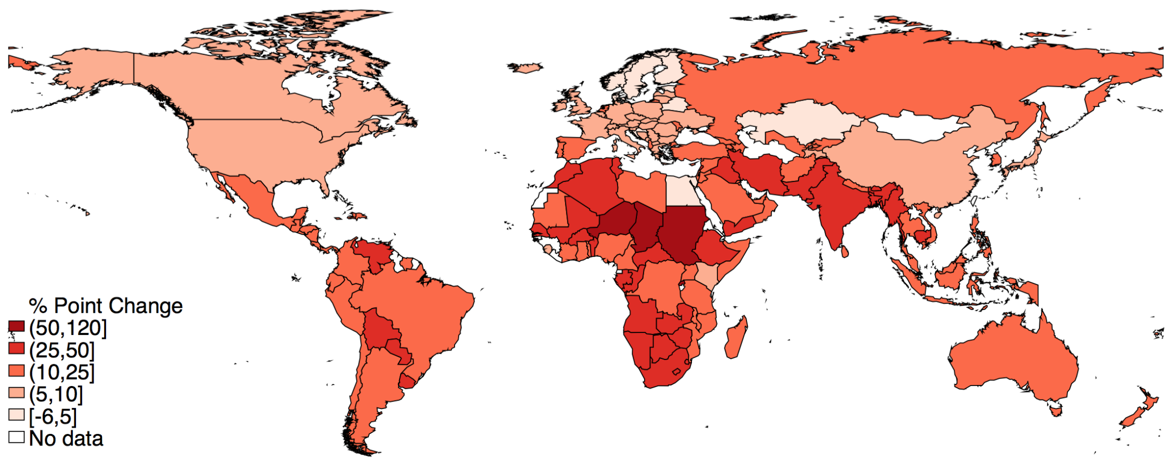
Notes: Table shows model simulations of the willingness-to-pay to avoid the effects of climate change. The full set of country-level results are shown in Appendix Tables A-39 to A-47.

Figure 13: Willingness-to-Pay to Avoid Climate Change



Notes: Map shows model simulations of the willingness-to-pay to avoid the effects of climate change as a share of GDP. The full set of country-level results shown in this map are listed in Appendix Tables A-39 to A-47.

Figure 14: Projected Percentage Change in Food Prices



Notes: Map shows model simulations of the change in food prices driven by climate change. The full set of country-level results shown in this map are listed in Appendix Tables A-48 to A-56.

Because the losses are concentrated in poor countries, global willingness-to-pay is only 1.7% of GDP. However, the population-weighted average global losses are 4.7% of GDP, and the population-weighted average for countries in the bottom quartile of income is 8.8% of GDP. The interpretation of this number is that climate change will cost the average person in the poorest quartile of the world nearly 9% of their income. Note that these results account neither for the costs of firm-level adaptation investments nor for the benefits of anticipated economic growth, both of which will be included in Section 7.6.

7.5 Low Trade Cost Counterfactual

The analysis of sectoral reallocation and aggregate productivity in Sections 7.3 and 7.4 demonstrates that openness to trade mitigates the harm from climate change by counteracting 'the food problem.' To further investigate the magnitude to which facilitating trade could contribute to climate change adaptation, I run an additional counterfactual exercise in which I replace the estimated matrix of bilateral trade costs, τ_{jkn}, with a uniform low value representing increased openness to trade. In particular, I set the cost of all bilateral trade for both manufacturing and agriculture at 100%. I choose this number rather than 0% to acknowledge the fact that some level of shipping costs, regulatory discrepancies, and language barriers are inherent to cross-country trade, so no amount of policy intervention could make trade perfectly costless. A 100% tariff-equivalent trade cost is toward the low end of the estimated distribution - approximately equal to the cost I estimate for shipping food from Belgium to Australia. I choose this value to represent an ambitious, yet realistically feasible, change in global trade policy.

To disentangle the benefits of trade for climate change adaptation from the more general gains from trade, I rescale each country's vector of sectoral productivity parameters, Z_{jk}, such that I continue to match the baseline levels of GDP per capita in the initial equilibrium. Note, however, that without the estimated high barriers to trade in developing countries the model can no longer match the observed global pattern of the agriculture share of GDP. In this hypothetical world of increased openness, developing countries import substantially more food from richer countries with high relative productivity in agriculture even in the absence of climate change.

Table 9: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Rwanda	-.434	-.387	-.086
Central African Republic	-.428	-.356	-.037
Chad	-.25	-.226	-.032
Malawi	-.225	-.225	-.119
Zimbabwe	-.223	-.212	-.074
Zambia	-.208	-.199	-.001
Ethiopia	-.171	-.169	-.091
Sierra Leone	-.13	-.164	-.105
India	-.085	-.082	-.013
World	-.018	-.017	-.013
Poorest Quartile	-.092	-.088	-.029

Notes: Table shows model simulations of the willingness-to-pay to avoid the effects of climate change under different scenarios - autarky, estimated global barriers to trade, and an alternative scenario at which all bilateral trade costs are set at a low level typical of OECD countries. The full set of country-level results are shown in Appendix Tables A-57 to A-65.

Table 9 shows the WTP to avoid climate change under different trade cost scenarios for a select subset of countries especially vulnerable to climate change. Appendix Tables A-57 to A-65 show these counterfactuals for the full range of countries. Two things about these results are worth noting. First, as shown in Table 9, reducing trade barriers dramatically reduces the costs of climate change in the hardest-hit countries. Overall, the WTP for the average person in the lowest quartile of global income is only 2.9%, relative to 8.8% in the estimated trade cost case.

Second, the effects of openness to trade vary substantially across countries. For 40 countries representing 15.1% of the global population, WTP to avoid climate change as a share of GDP is *higher* in the low trade cost scenario.[46] The intuition

[46]To be clear, these countries still experience overall gains from trade. But once those general gains are netted out, they suffer larger climate change damages in this scenario.

for this result is as follows. When trade barriers are high and local consumption depends mostly on local production, the effects of deteriorating productivity are also concentrated locally. Conversely, more trade makes the world more interdependent and dilutes the effects of a local shock across many countries. If consumption in Austria is more linked to production in Zimbabwe, then Austrian consumers suffer more from shocks that hit Zimbabwe. Conversely, Zimbabwean consumers insulate themselves from the local shock by consuming a more diversified global portfolio of products.

Overall, trade reduces the aggregate global willingness-to-pay to avoid climate change by 7.4% relative to autarky under existing global trade policy, and by 30.7% under the specified alternative assumption of freer trade. This pattern holds much more starkly in poor countries. For the average person in the poorest quartile of the world, trade reduces WTP by 4.5% relative to autarky under existing policy, but by 68.2% under freer trade. I discuss possible policy mechanisms to realize these gains in Section 9.

7.6 Future Projections

The results in Sections 7.1 to 7.5 use projections for future temperature change, but hold the baseline global economy fixed at the present day equilibrium. In this section, I endeavor to better represent the future baseline in 2080 by allowing global income levels to evolve according to projections from the Shared Socioeconomic Pathway (Scenario Three) developed by Cuaresma (2017) of the International Institute for Applied Systems Analysis.[47]

Allowing for economic growth to take place has two important effects on the aggregate consequences of climate change. First, the agriculture share of GDP declines as countries grow richer due to nonhomothetic preferences for food, reducing the aggregate consequences of agriculture-specific productivity shocks. I capture this effect in the model by applying projected income growth to 2080 as sector-neutral increases in the baseline values of Z_{jk}. Second, my results from Section 4 imply that sensitivity to temperature for manufacturing and services firms declines markedly as countries become richer. I capture this by re-evaluating the sensitivity to temperature shown in Figures 5 and 6 at 2080 levels of log GDP per capita. Appendix Figures A-25 and A-26 show that the effects of temperature on non-agricultural productivity accounting for adaptation are substantially muted, even in this relatively low growth scenario that projects only slightly more than a doubling of global income between 2015 and 2080.

Table 10 shows the impact of expected economic growth on the agriculture share of GDP and expected willingness-to-pay. Appendix Tables A-66 to A-74 show the results for all countries. The willingness-to-pay numbers in Columns 5 and 6 of Table 10 also incorporate the firm-level adaptation costs shown in Appendix Figure A-18, thus accounting more comprehensively for the anticipated costs as

[47]Use of the Shared Socioeconomic Pathways in future projections of climate change damages follows from the work of Carleton et al. (2018).

Table 10: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counterfactual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Central African Republic	1.47	.299	.287	.094	-.436	-.316
Rwanda	1.14	.409	.39	.322	-.394	-.366
Zimbabwe	4.17	.302	.122	.14	-.248	-.111
Malawi	2.84	.436	.309	.357	-.244	-.167
Zambia	1.52	.36	.28	.318	-.233	-.181
Chad	1.13	.257	.213	.243	-.226	-.221
Sierra Leone	1.49	.139	.177	.173	-.204	-.146
Ethiopia	1.23	.359	.333	.376	-.19	-.182
India	3.24	.161	.087	.106	-.082	-.045
Poorest Quartile	3.05	.199	.126	.144	-.1	-.062
World	2.2	.038	.025	.028	-.027	-.015

Notes: Table shows model simulations of the effects of projected economic growth on the agriculture share of GDP and the willingness-to-pay to avoid climate change in select countries. Economic growth projections come from Cuaresma (2017). The full set of country-level results are listed in Appendix Tables A-66 to A-74.

well as benefits of adaptation.[48] This particular future scenario includes little to no projected growth for many currently poor countries, allowing for contrast with those that grow faster. This comparison shows the importance of economic growth in mitigating the harm from climate change. Table 10 shows that Zimbabwe and Malawi get substantially richer in this projection, and their agriculture share of GDP and climate change damages decline markedly. In contrast, climate change continues to be very harmful to countries that grow slowly, such as Rwanda and Chad.

The results in Table 10 show that the aggregate global WTP for climate change is 2.7% of GDP at current global income levels and 1.5% at future projected incomes. The average WTP for a person in the bottom quartile of the world is 10.0% from the present baseline and 6.2% from the future baseline. To summarize the importance of the distributional consequences of climate change, I follow Jones and Klenow (2016) to calculate the willingness-to-pay of a Rawlsian social plan-

[48]I exclude this revealed preference measure of firm-level adaptation costs from Tables 8 and 9 because they are calculated as a share of manufacturing and services output, which vary dramatically as a share of baseline total output in the low trade cost scenario, thus complicating the comparison of climate change damages between the estimated and low trade cost counterfactuals.

ner taking the certainty equivalent of being any person in the world with random probability.[49] The Rawlsian welfare losses from climate change are 6.2% of global GDP from the present income baseline and 3.6% of global GDP from the future baseline, more than twice as high as the aggregate willingness-to-pay calculated by summing across agents.

7.7 Model Robustness

I consider robustness to three alternative model assumptions in Appendix G. In Appendix G.1 I represent subsistence requirements for food using generalized Stone-Geary preferences instead of the nonhomothetic CES specification in the baseline model. In Appendix G.2 I use lognormal, rather than Frechet, distributions to represent sector-country productivities across varieties. In Appendix G.3 I lay out a version of the model with heterogeneous workers by skill type in each country. Appendix Table A-76 shows that the main counterfactual simulation results are very similar under the first two alternative modeling assumptions. The third extension with heterogeneous workers is not amenable to quantification, but I demonstrate the qualitative robustness of the main results and use the model extension to explore additional dimensions of the implications of climate change for comparative advantage across sectors and the distributional impact on low and high skill workers.

8 Supporting Empirical Evidence

In this section, I present country-level panel regression evidence consistent with the model counterfactuals. In particular, my results in Section 7 suggest that the 'food problem' outweighs the trade response, on average, in driving sectoral reallocation due to climate change. This finding is supported by the simulated method of moments inference that underlies my parameter estimates, is consistent with both cross-sectional and historical patterns of sectoral specialization in the world, and is further bolstered by existing empirical evidence that aims to isolate the causal effect of agricultural productivity on structural transformation. In particular, Gollin, Hansen and Wingender (2018) proxy for improvements in agricultural productivity using variation in the development, diffusion, and climatic suitability for high-yielding crop varieties and Bustos, Caprettini and Ponticelli (2016) study the introduction of genetically engineered soybean seeds in Brazil. Both papers find that rising agricultural productivity drove labor out of agriculture and into industry. Here, I present evidence suggestive of the converse more representative of climate change - that declines in agricultural productivity increase the agriculture share of GDP and labor on average relative to the counterfactual.

Table 11 summarizes the data sources used in this part of my analysis.[50] Fol-

[49] Following Jones and Klenow (2016) I use log utility in this calculation.

[50] I use BEST temperature data with a 1°global grid in this specification because aggregating GMFD temperature data from a 0.25°grid for every country worldwide exceeds my available

Table 11: Country-Level Panel Data

Variable	Data Source
Temperature	Berkeley Earth Surface Temperature Dataset
Ag Share of GDP	World Bank
Ag Share of Labor Force	International Labour Organization
Food Share of Imports	UN Comtrade
GDP	World Bank

Notes: Data covers 164 countries from 1960-2012 with varying coverage by country and dataset. Economic data from all sources above are retrieved from the World Bank Databank.

lowing Schlenker and Roberts (2009), I use "growing degree days" (GDD) between 0°C and 29°C and "killing degree days" (KDD) above 29°C as temperature transformations representing positive and negative shocks to agricultural productivity. I aggregate GDD and KDD to the country level for each year weighting by each pixel's share of cropland.[51]

I estimate the following panel regression with observations at the country-year level for four separate outcome variables - log GDP, food share of imports, agricultural share of GDP, and agricultural share of labor:

$$Y_{it} = \beta_1 GDD_{it} + \beta_2 KDD_{it} + \delta_i + \kappa_t + \epsilon_{it} \tag{24}$$

The regression exploits idiosyncratic variation in weather controlling for country fixed effects, δ_i, and year fixed effects, κ_t to estimate the plausibly causal effect of shocks to agricultural productivity. I weight observations by their share of the global agricultural labor force to recover expected reallocation for the average farm worker in the world.

The results in Table 12 are broadly consistent with my model simulations in Section 7. The composition of imports shifts toward food in response to negative agricultural productivity shocks (KDD), and away from food in response to positive shocks (GDD), but the magnitudes of these changes are small. Consistent with an important role for 'the food problem,' the agriculture share of GDP and labor rise with KDD and fall with GDD, with magnitudes roughly similar to those in the

computational resources.

[51]Following standard procedure in estimating temperature effects on agricultural productivity, degree days are calculated by fitting a sinuisoidal curve through daily minimum and maximum temperature, and then integrating the proportion of each day above a certain threshold.

Table 12: Country-Level Panel Regression

	(1) log(GDP)	(2) Food Share of Imports	(3) Ag Share of GDP	(4) Ag Labor Share
KDD X 100	-0.121	0.00258	0.00875	0.00991
	(-2.31)	(0.64)	(1.08)	(1.55)
GDD X 100	0.0505	-0.00429	-0.00140	-0.00138
	(1.64)	(-2.45)	(-1.54)	(-0.38)
Observations	3602	2916	3171	3715
Country FE	X	X	X	X
Year FE	X	X	X	X
Ag Labor Weights	X	X	X	X

Notes: t-statistics in parentheses. Reported Driscoll and Kraay (1998) standard errors are robust to heteroskedasticity, spatial correlation, and autocorrelation of up to 5 lags. Results come from estimating Equation 24 with crop-area weighted growing and killing degree days. Data covers 164 countries from 1960-2012 with varying coverage by country and outcome variable. Economic data from all sources above are retrieved from the World Bank Databank.

model. Here, the agriculture share of GDP rises by slightly under 1 percentage point for an agriculture-biased shock that reduces GDP by 12%. To construct a corresponding level of reallocation in my model simulations, I calculate that the agricultural population-weighted average change in the agricultural share of GDP for those countries suffering large declines in agricultural productivity ($<$10 percentage points) is +2.1 percentage points from an average agricultural productivity fall of 29.5%.[52]

The results from the country-level regressions are imprecise and insufficient in isolation to make full general equilibrium projections or welfare calculations relating to sectoral reallocation in response to climate change.[53] Taken together with the analysis in Sections 6 and 7 and the existing body of evidence, however, these results reinforce the important role of the 'food problem' in mediating the

[52]An additional feature of the regression that supports the approach taken in the model is the very similar coefficients estimated for the agriculture share of GDP and the labor force. These two shares are equivalent in my model because I allow wages to equalize across sectors, but the agriculture share of labor is generally higher in the data since agricultural wages tend to be lower. The similar coefficients in Table 12 suggest that projecting reallocation in ag GDP is informative for understanding labor reallocation even if the levels of these two variables differ.

[53]I show results for the unweighted regressions in Appendix Table A-75. I gain precision in the unweighted specification because the agriculture labor share weights are missing for a nontrivial share of the observations, but have a less interesting interpretation of the coefficients as effects on the average country in the world rather than on the average unit of agricultural labor.

aggregate consequences of climate-driven agricultural productivity shocks.

9 Policy Implications

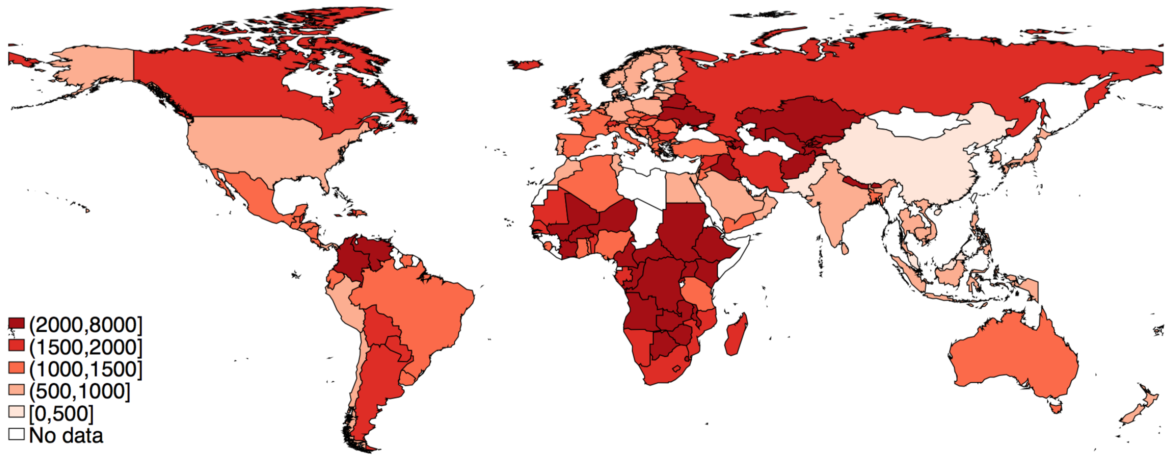
This paper has three sets of implications relevant to policy on climate change and development. First, the results inform cost-benefit analysis on policies to reduce greenhouse gas emissions and avoid damage from climate change. These results are not a comprehensive evaluation of the costs of climate change - I omit international migration, uncertainty, health effects, and non-temperature effects such as storms and sea-level rise, among other topics, from my analysis. I do, however, address an existing challenge in the literature by estimating global reductions in aggregate productivity and calculating their welfare consequences in a framework that accounts for reallocation of economic activity between agriculture and non-agriculture.

Second, my results inform decisions about the best way to channel efforts to adapt directly to the consequences of climate change. If it were true that agricultural activity is likely to shift substantially away from hot developing countries, optimal investments in adaptation might focus on retraining farm workers to transition to non-agricultural occupations. Instead, my finding that climate change is more likely to increase specialization in agriculture in hot countries underscores the urgent need to reduce the temperature-sensitivity of production through technology, irrigation, heat-resistant crop varieties, or other means. The agricultural productivity consequences projected by Cline (2007) will take place gradually and worsen far into the future, and need not be invariant to efforts to reduce them.

Third, and perhaps most importantly, my results speak to the importance of reducing barriers to trade in developing countries as a mechanism for climate change adaptation. The results in Section 7.4 suggest that the costs of climate change to the average person in the poorest quartile of the world could be reduced by more than half in a world with a plausible increase in openness to trade. Reducing tariffs would be one place to start, but tariffs account for a relatively small proportion of estimated trade costs. As Tombe (2015) documents at length, red tape barriers appear to be a far more important deterrent in many places. Figures 15 and 16 show data from the World Bank Ease of Doing Business Indicators on fees and delays associated with importing a container.

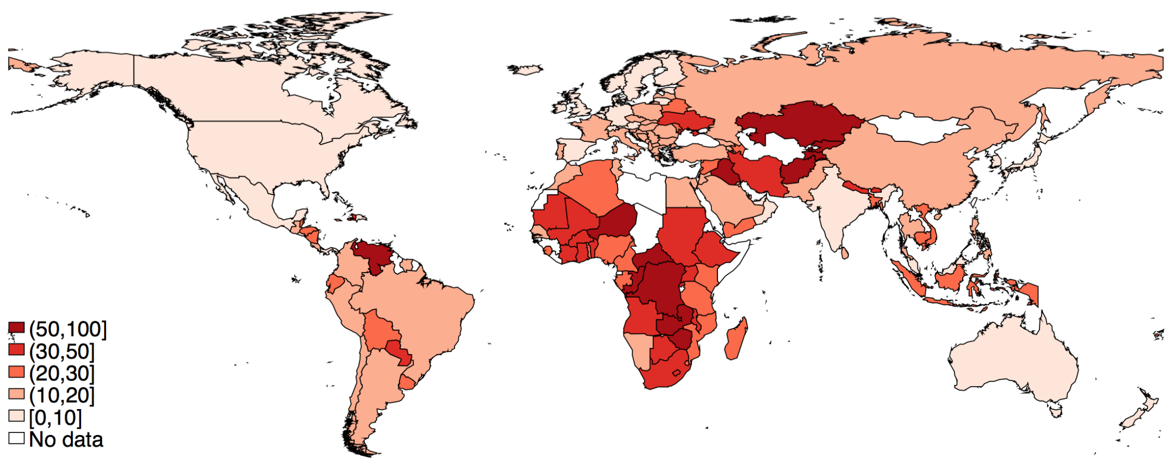
The average country in Sub-Saharan Africa requires 9 documents and over $2700 in fees for customs clearance, document processing, customs brokerage, terminal handling, and inland transport to import a 20-foot container of goods, exclusive of tariffs and unofficial payments. Importing a shipment to Sub-Saharan Africa also requires waiting an average of 37 days upon arrival at the border for compliance with customs clearance, inspection procedures, and document preparation, likely a prohibitive length of time for many food imports. These types of trade barriers do not involve international negotiations or physical constraints to shipping over long distances, and thus could be a relatively tractable place to target reforms that

Figure 15: Direct Costs to Import a 20-Foot Long Container (USD)



Notes: Figure shows the direct cost to import one container of goods. Costs include documents, administrative fees for customs clearance, terminal handling charges, and inland transport, but not tariffs or taxes. Data comes from the World Bank Ease of Doing Business index.

Figure 16: Days to Import a Container



Notes: Figure shows the average number of days required to import a container. Delays include customs clearance, government inspection procedures, and documentary compliance requirements. Data comes from the World Bank Ease of Doing Business Index.

could make a substantial impact on climate change adaptation.

10 Conclusion

The standard intuition in economics is that reallocation improves outcomes. Falling productivity raises prices and encourages substitution to other products. But this logic does not hold for broad categories of necessary consumption, such as food. If a fall in productivity causes the price of corn to rise sharply, people can adapt by eating more rice. But when people become poorer and the relative price of food rises, they cannot compensate by substituting away from food.

This paper investigates the importance of subsistence requirements for food for the general equilibrium and aggregate productivity effects of climate change. I show that climate change predominantly shifts comparative advantage in agriculture away from the equator as the effects of extreme temperatures on non-agricultural productivity are generally smaller than those on agriculture. On average, however, the effect of a large decline in productivity concentrated in agriculture moves specialization toward, rather than away from, agriculture because of the special properties of consumer preferences for food. Countries with large climate change productivity impacts in agriculture that are more open to trade suffer less because they are more able to increase imports of food and shift production toward other sectors. Overall, reducing barriers to trade could reduce the losses from climate change by more than half for the poorest quarter of the world's population.

I conclude with several suggestions for future research. First, while my work is informative about the cost-benefit analysis of climate change mitigation, additional effort is required to integrate these general equilibrium effects directly into calculations of the social cost of carbon. Second, while my analysis shows that reducing barriers to trade is a necessary condition to induce sectoral reallocation to curtail the costs of climate change, I cannot conclude that it is sufficient. A low trade cost counterfactual in which specialization in agriculture shifts away from the equator still relies on uncertain assumptions about diminishing returns to expanding production of tradable manufactured goods in developing countries, as well as on the availability of complementary inputs such as soil quality and arable land in cold countries experiencing improved temperature suitability for agriculture. A final topic concerns the political economy of trade policy regarding food. Policymakers often prioritize "food security" as a stated aim, implying a preference for domestic food production secure from interference by foreign countries. To the extent that this goal conflicts with adaptation to climate change in light of large declines in agricultural productivity in certain regions, it may be worth examining this tradeoff more closely, both in practice and in perception.

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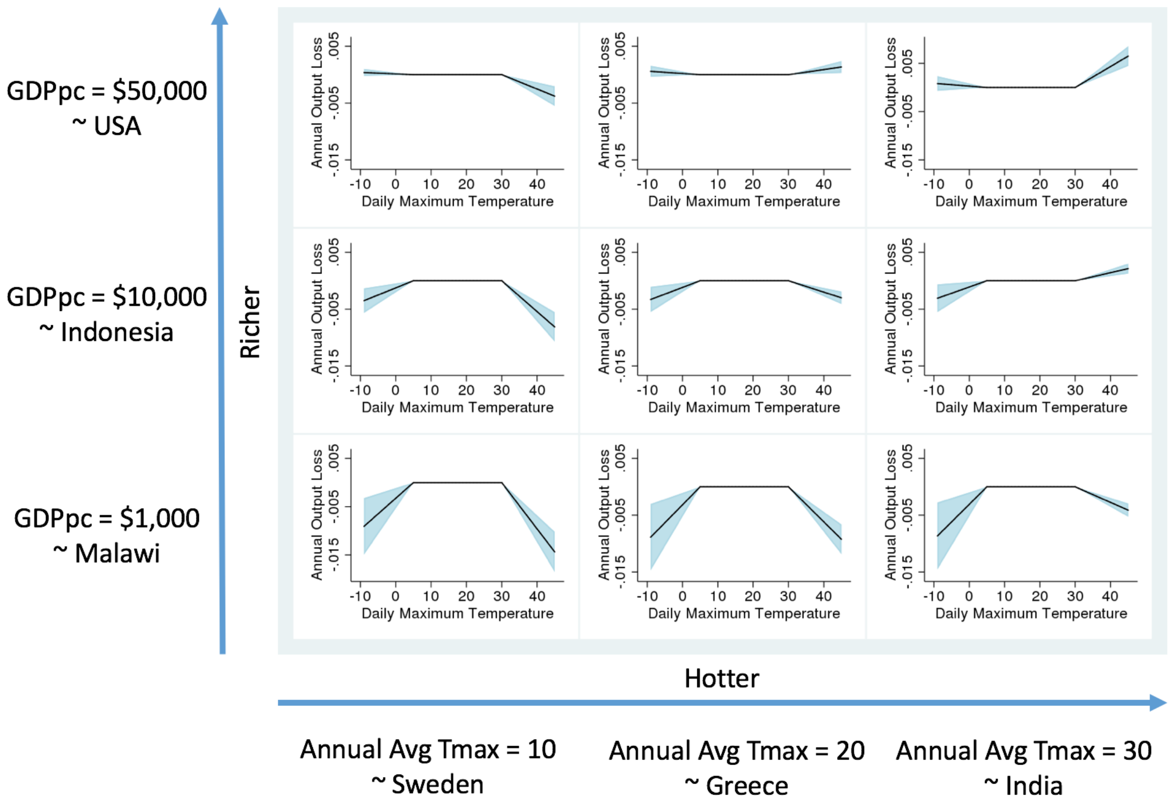
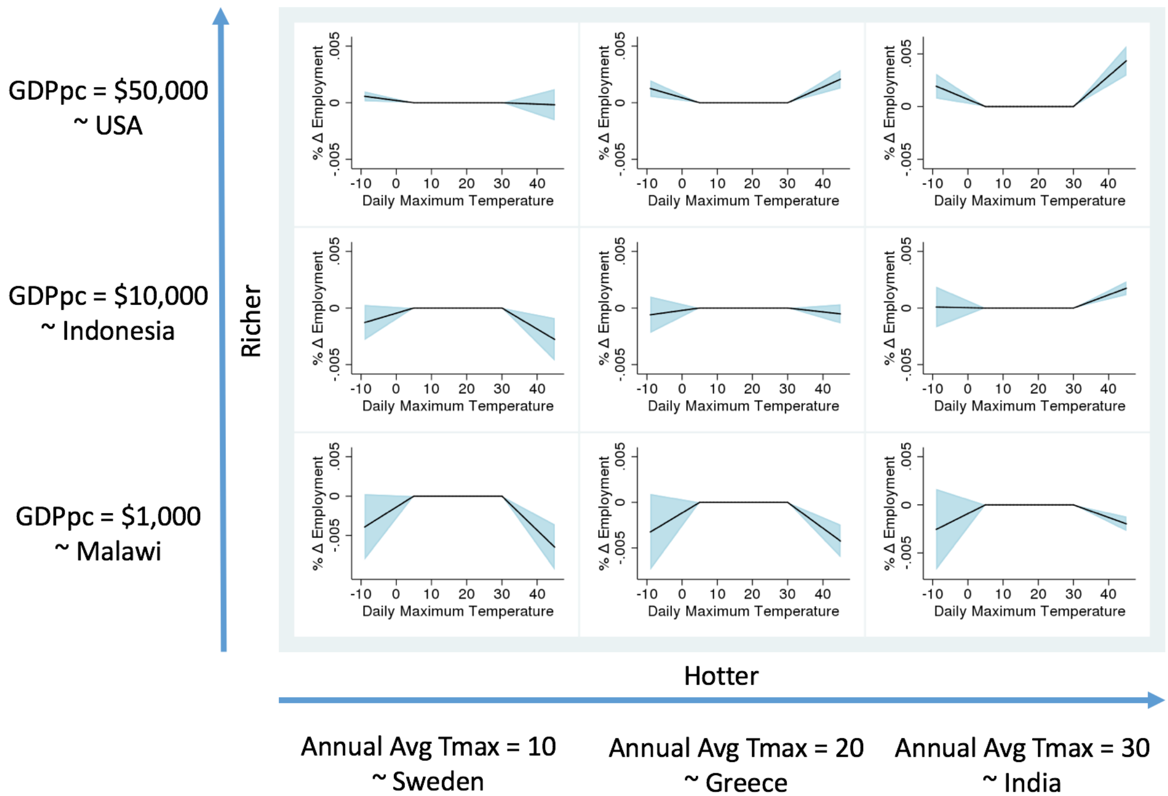
Appendix A: Additional Regression Results

Figure A-1: Predicted Heterogeneous Response of Annual Manufacturing Revenue to Daily Maximum Temperature



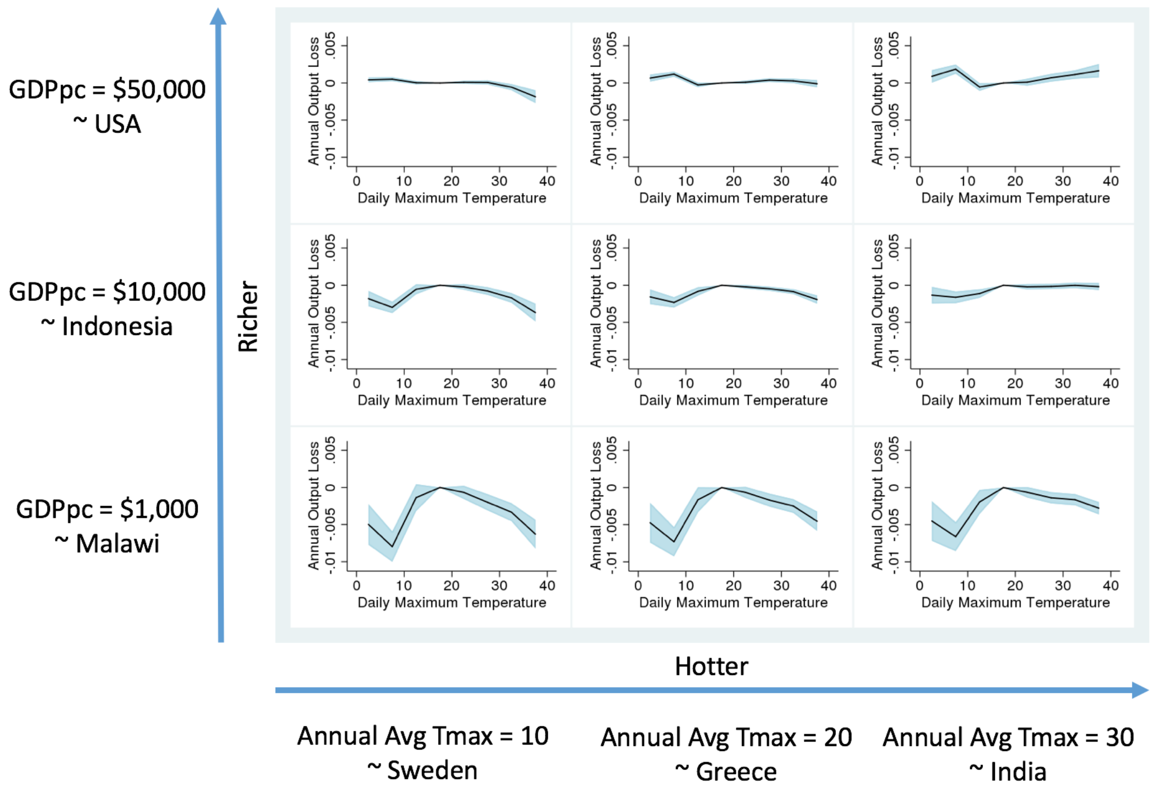
Notes: Figure shows the predicted effect of temperature on the log of manufacturing revenues at varying levels of income and long-run average temperature by evaluating the interacted regression from Column 3 of Table 2. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-2: Predicted Heterogeneous Response of Annual Manufacturing Employment to Daily Maximum Temperature



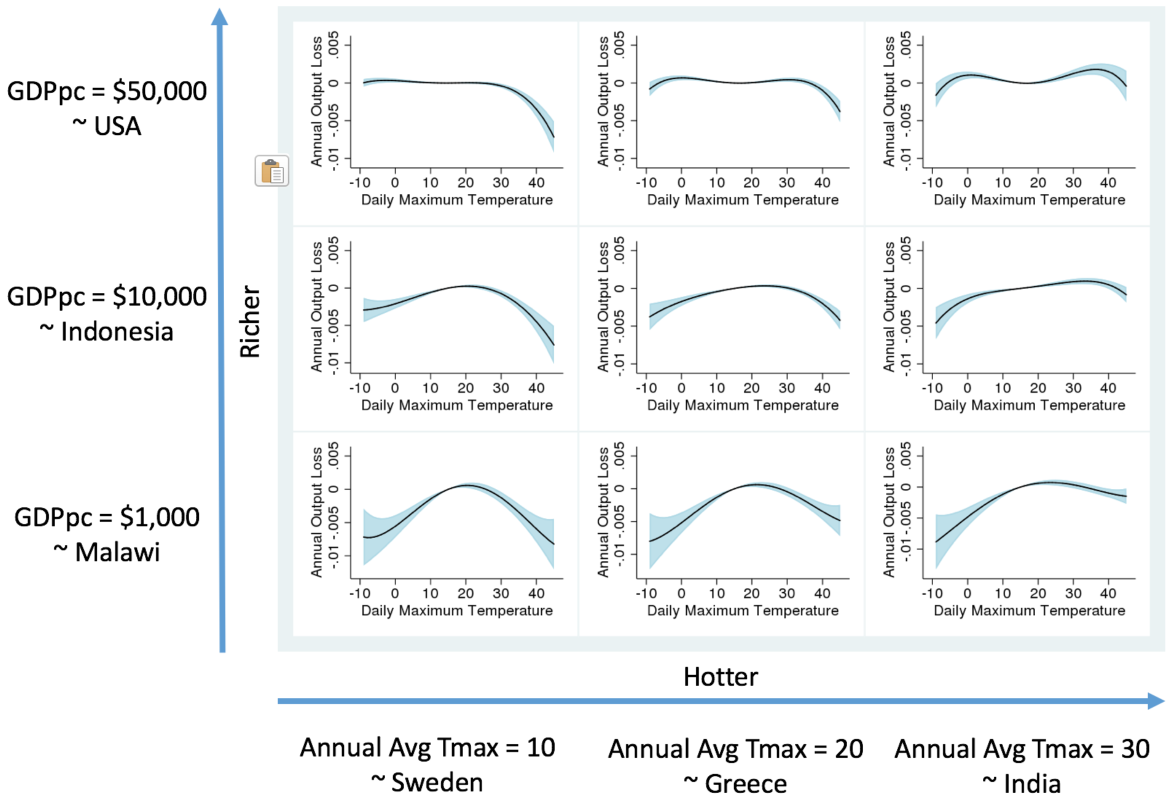
Notes: Figure shows the predicted effect of temperature on the log of manufacturing employment at varying levels of income and long-run average temperature by evaluating the interacted regression from Column 4 of Table 2. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-3: Predicted Heterogeneous Response of Annual Manufacturing Revenue Per Worker to Daily Maximum Temperature



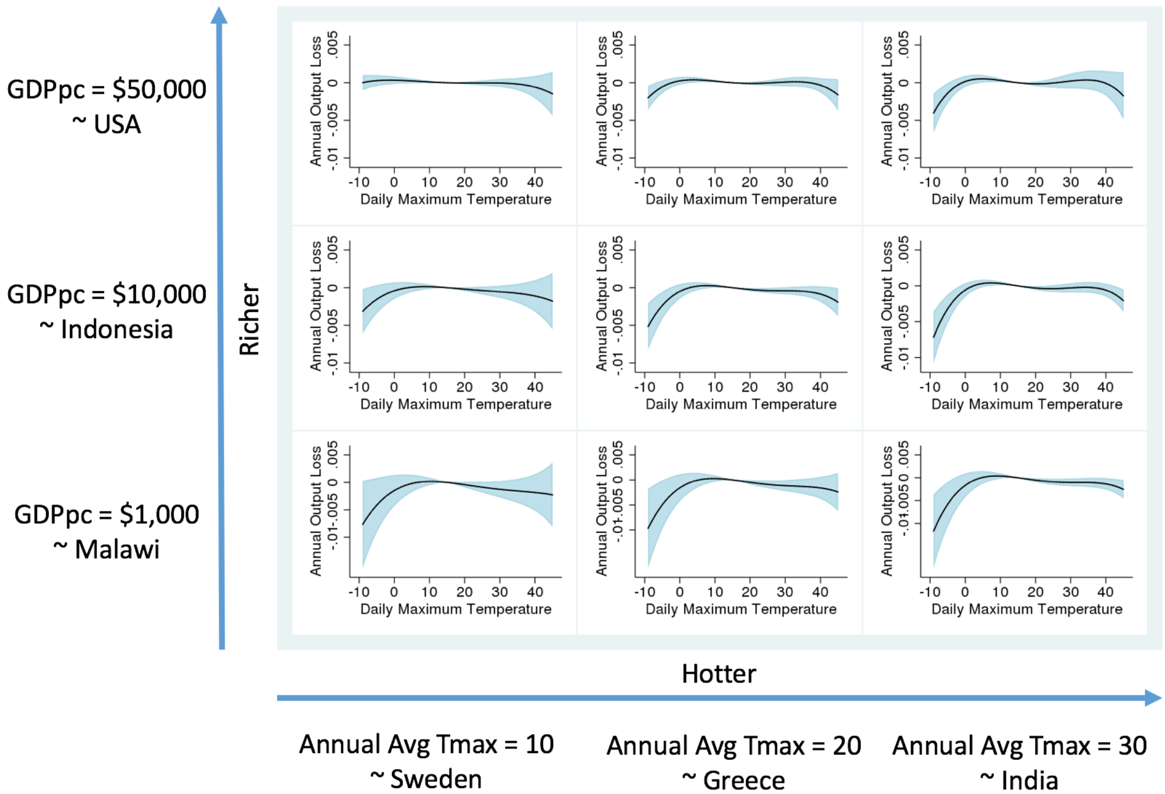
Notes: Figure shows the predicted effect of temperature on manufacturing revenue per worker at varying levels of income and long-run average temperature using bins of daily maximum temperature in the specification from Equation 8.Days are divided into 5°C bins. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-4: Predicted Heterogeneous Response of Annual Manufacturing Revenue Per Worker to Daily Maximum Temperature



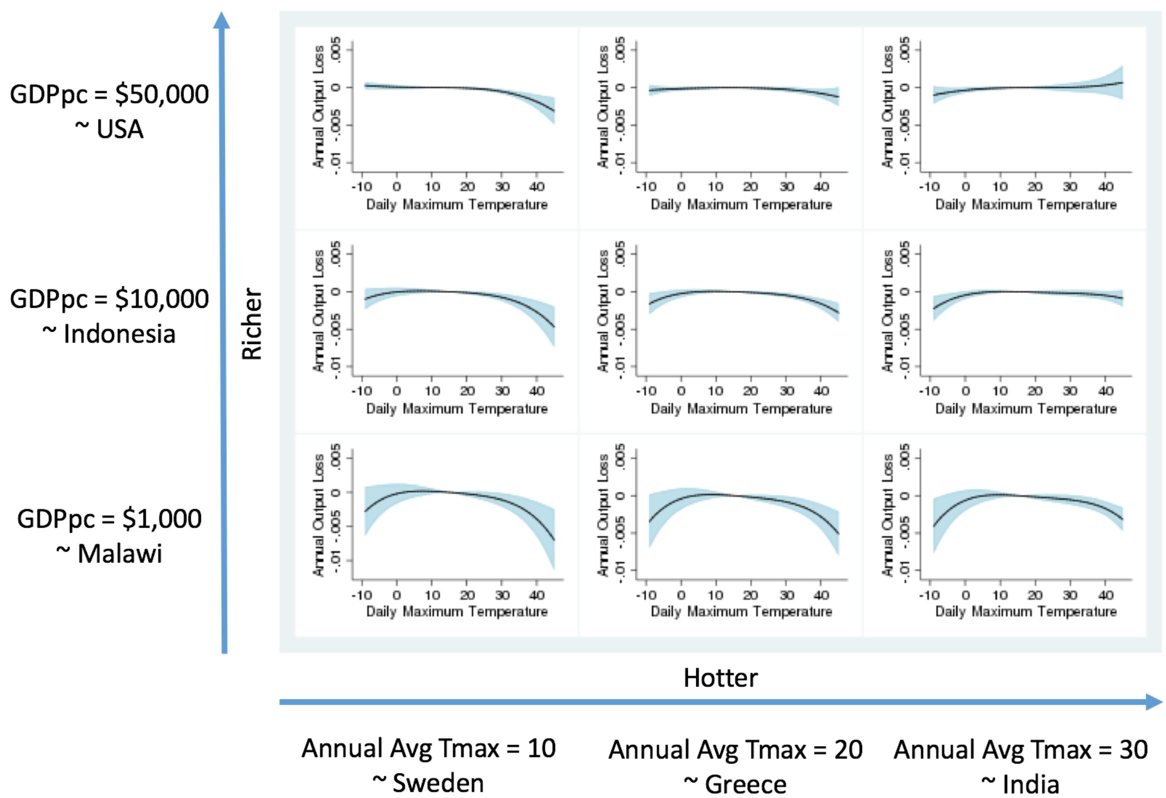
Notes: Figure shows the predicted effect of temperature on manufacturing revenue per worker at varying levels of income and long-run average temperature using a polynomial of degree four in daily average temperature in the specification from Equation 8.Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-5: Predicted Heterogeneous Response of Annual Manufacturing Revenue Per Worker to Daily Maximum Temperature - State-by-Year FE



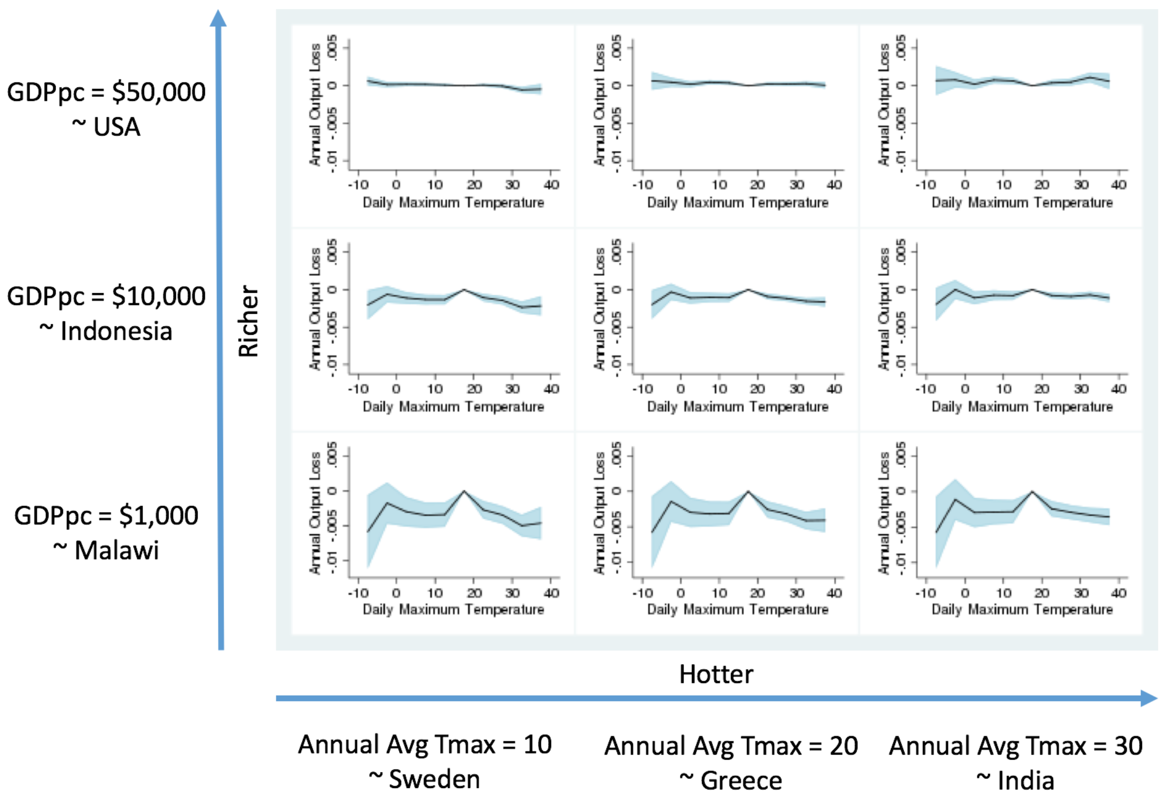
Notes: Figure shows the predicted effect of temperature on manufacturing revenue per worker at varying levels of income and long-run average temperature using the specification from Equation 8 with state-by-year fixed effects and a polynomial of degree four in daily maximum temperature. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-6: Predicted Heterogeneous Response of Annual Manufacturing/Services Revenue Per Worker to Daily Maximum Temperature - State-by-Year FE



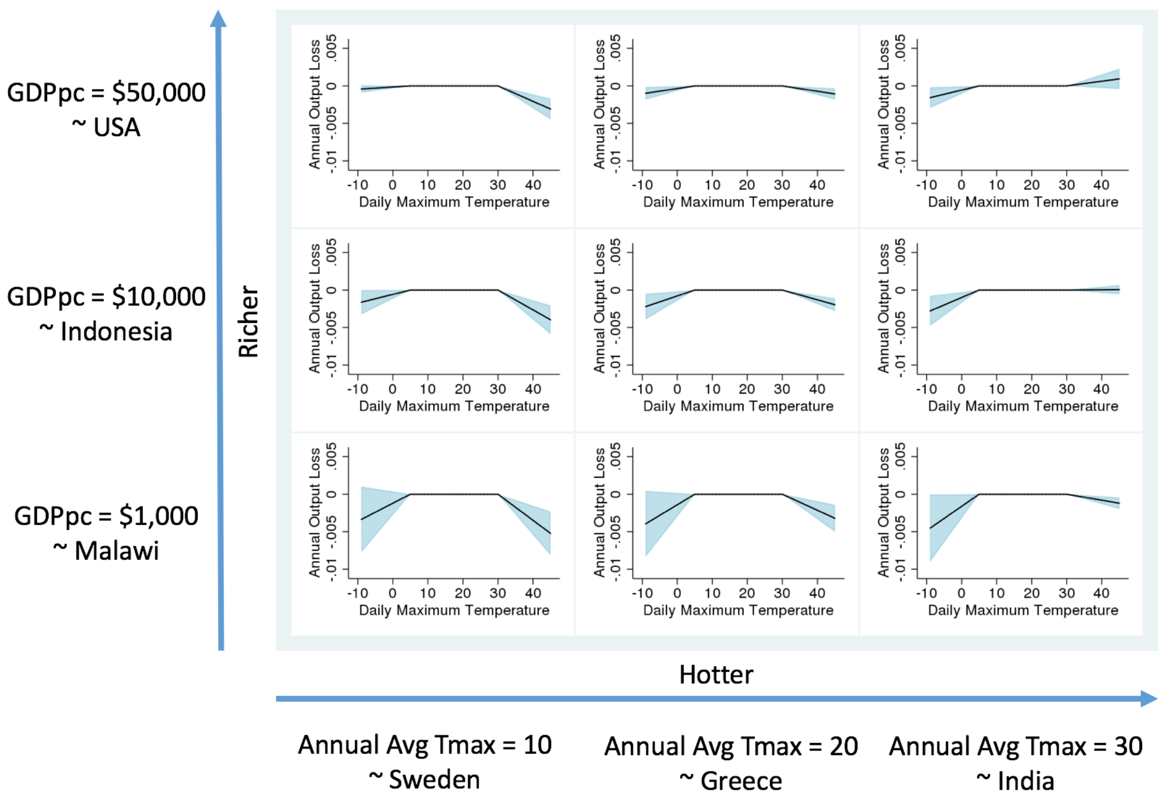
Notes: Figure shows the predicted effect of temperature on revenue per worker at varying levels of income and long-run average temperature for a pooled sample of manufacturing and services firms using the specification from Equation 8 with state-by-year fixed effects and a polynomial of degree four in daily maximum temperature. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-7: Predicted Heterogeneous Response of Annual Manufacturing/Services Revenue Per Worker to Daily Maximum Temperature - State-by-Year FE



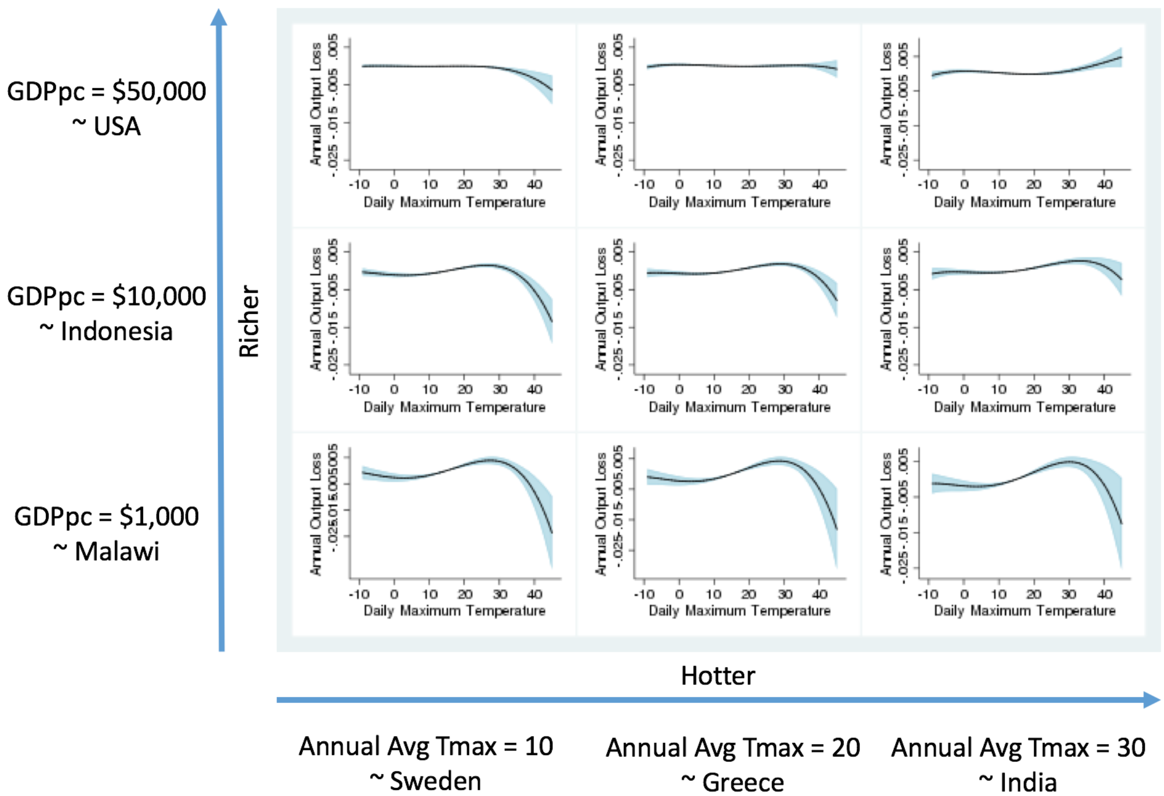
Notes: Figure shows the predicted effect of temperature on revenue per worker at varying levels of income and long-run average temperature for a pooled sample of manufacturing and services firms using the specification from Equation 8 with state-by-year fixed effects and bins of daily maximum temperature. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-8: Predicted Heterogeneous Response of Annual Manufacturing Revenue Per Worker to Daily Maximum Temperature - Controls for Capital



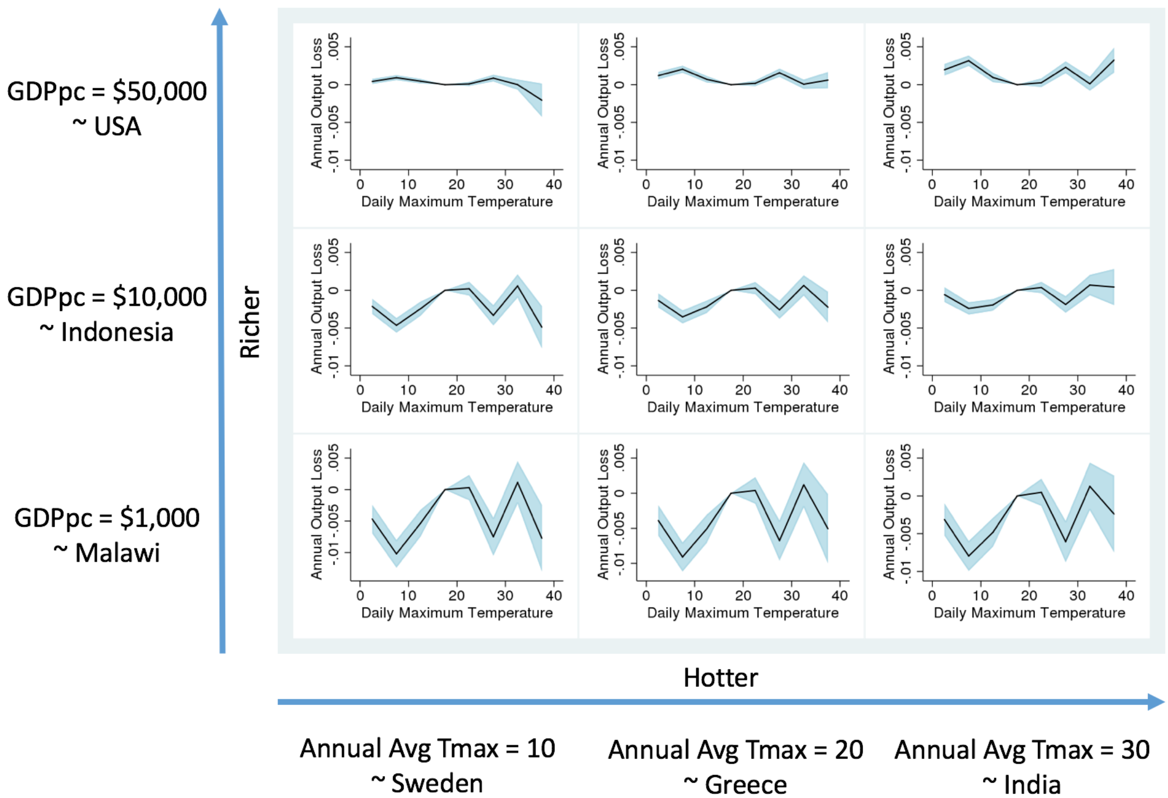
Notes: Figure shows the predicted effect of temperature on manufacturing revenue per worker at varying levels of income and long-run average temperature using the specification from Equation 8 with controls for capital. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-9: Predicted Heterogeneous Response of Annual Services Revenue Per Worker to Daily Maximum Temperature



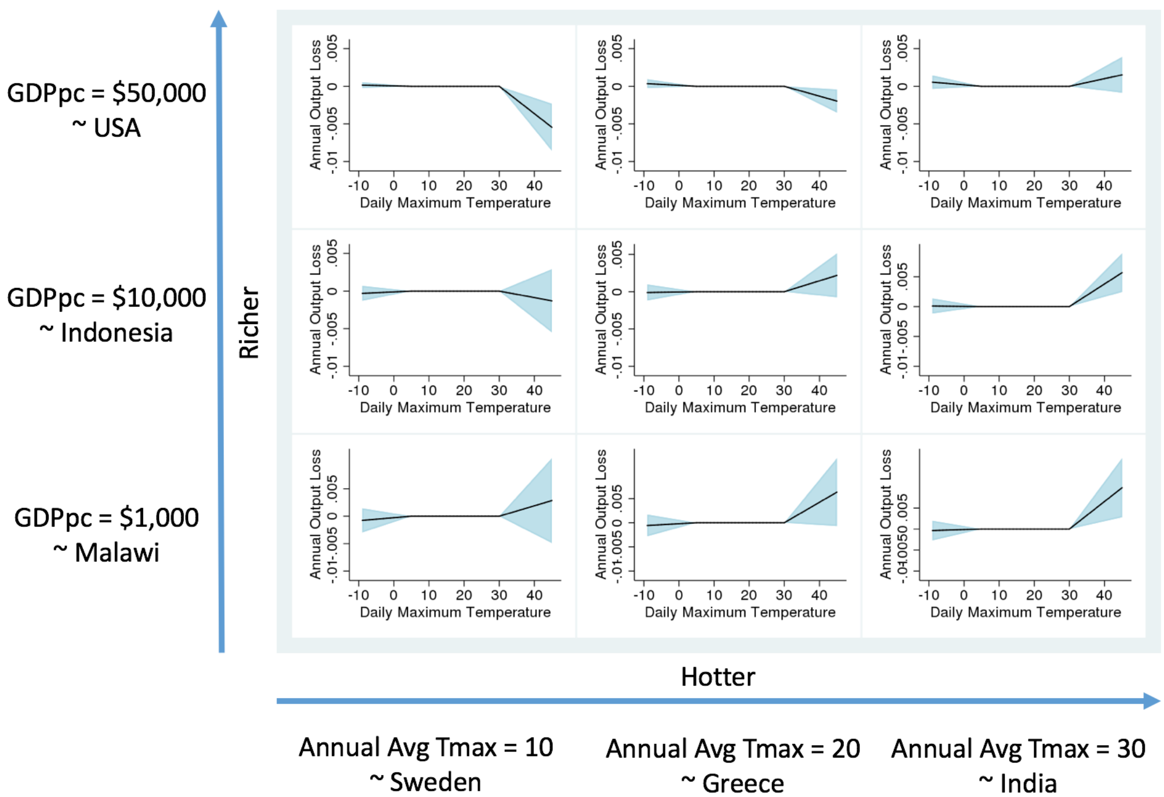
Notes: Figure shows the predicted effect of temperature on services revenue per worker at varying levels of income and long-run average temperature using the specification from Equation 8 with a polynomial of degree four in daily maximum temperature. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Figure A-10: Predicted Heterogeneous Response of Annual Services Revenue Per Worker to Daily Maximum Temperature



Notes: Figure shows the predicted effect of temperature on services revenue per worker at varying levels of income and long-run average temperature using the specification from Equation 8 with bins of daily maximum temperature. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

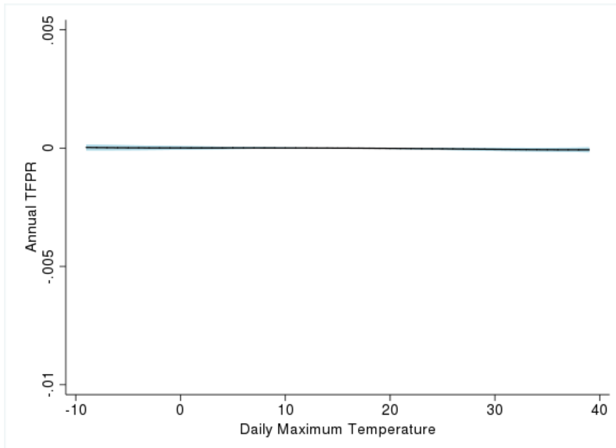
Figure A-11: Predicted Heterogeneous Response of Annual Services Revenue Per Worker to Daily Maximum Temperature



Notes: Figure shows the predicted effect of temperature on services revenue per worker at varying levels of income and long-run average temperature using the specification from Equation 8. Outcome variables come from data sources listed in Table 1 and temperature data is from GMFD.

Appendix B: U.S. Results

Figure A-12: Estimated Response of U.S. Annual Manufacturing TFPR to Daily Maximum Temperature



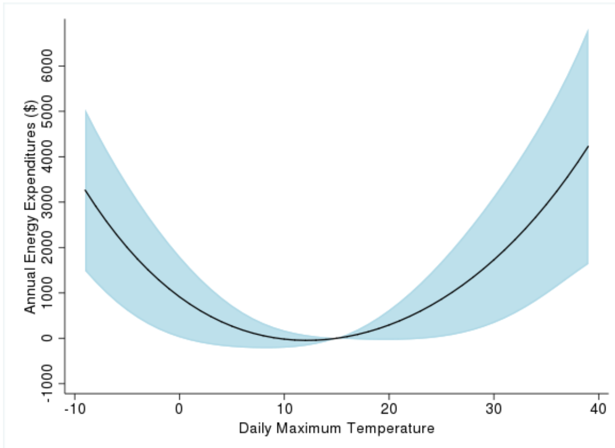
Notes: Figure shows the estimated effect of temperature on manufacturing TFPR using the specification from Equation 7 with a polynomial of degree four in daily maximum temperature. Outcome data comes from the Annual Survey of Manufacturers and Census of Manufacturers from the U.S. Census Bureau. Temperature data is from GMFD.

Table A-1: U.S. Results

	Revenue/Worker	Revenue	Employment	TFPR	Revenue/Worker	Revenue/Worker
TMax-30	-0.0000109	0.0000220	0.0000330	0.00000134	-0.0000422	0.0000110
	(-2.21)	(2.01)	(3.49)	(0.33)	(-2.97)	(0.46)
5-TMax	0.0000365	0.0000338	-0.00000269	-0.00000685	-0.0000226	0.000154
	(5.65)	(2.65)	(-0.26)	(-1.30)	(-1.71)	(3.56)
Observations	2852000	2852000 2852000	2852000	2852000	2852000	
Firm FE	X	X	X	X	X	X
Country X Year FE	X	X	X	X	X	X
State X Year FE					X	
Sales Weighting						X

Notes t-statistics in parentheses. Dependent variables all in logs. Standard errors two-way clustered at the firm and county-by-year level. Estimates use the regression model from Equation 7 with outcome variable data from 1976-2014 from the Annual Survey of Manufacturers and Census of Manufacturers from the U.S. Census Bureau and temperature data from the Global Meteorological Forcing Dataset.

Figure A-13: Estimated Response of U.S. Annual Manufacturing Plant-Level Energy Expenditures to Daily Maximum Temperature



Notes: Figure shows the estimated effect of temperature on manufacturing energy expenditures using the specification from Equation 7 with a polynomial of degree four in daily maximum temperature. Energy expenditures are the sum of cost of fuels and electricity expenditures in the Annual Survey of Manufacturers and Census of Manufacturers from the U.S. Census Bureau. Temperature data is from GMFD.

Table A-2: U.S. Energy Results

	log(Energy Expenditure)	Energy Expenditures	log(Energy Expenditures)	Energy Expenditures
TMax-30	0.0000822	0.0000890	251.1	6056
	(6.03)	(3.24)	(4.45)	(1.32)
5-TMax	0.0000108	0.00000184	490.8	13840
	(0.78)	(0.04)	(3.57)	(1.69)
Observations	2852000	2852000	2852000	2852000
Firm FE	X	X	X	X
Country X Year FE	X	X	X	X
Sales Weighting		X		X

Notes: t-statistics in parentheses. Standard errors two-way clustered at the firm and county-by-year level. Estimates use the regression model from Equation 7 with outcome variable data from 1976-2014 from the Annual Survey of Manufacturers and Census of Manufacturers from the U.S. Census Bureau and temperature data from the Global Meteorological Forcing Dataset. Dependent variable is the sum of electricity expenditures and cost of fuels, in logs or levels.

Appendix C: China Results

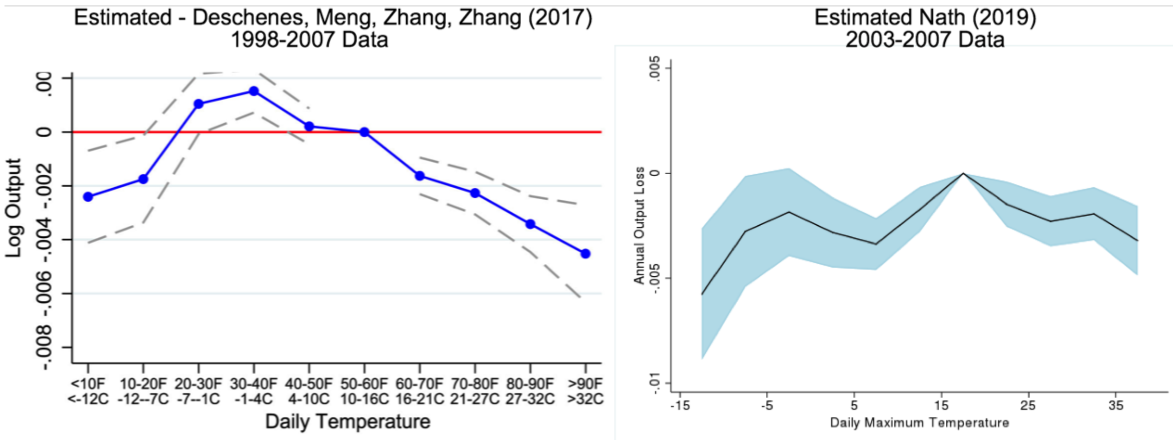
This section explains the data quality issues that lead me to estimate the results in Section 4.1 excluding data from China. At a high level, I find evidence consistent with the conclusions of Chen, Chen, Hsieh and Song (2019) that Chinese micro-data after 2007 are unreliable due to systematic manipulation by local officials. The details are as follows.

To start with, Zhang, Deschenes, Meng and Zhang (2018) analyze data from China for the years 1998-2007 and find that both cold and hot temperatures harm output and productivity, consistent with my findings. Using the overlapping subset of years from my data, which goes from 2003-2012, I am able to replicate their findings fairly closely, as shown in Appendix Figure A-14. Notably, I am also able to use my main results from the rest of my global data in Figure 3 to predict the response of output to temperature in China based on their income level and average climate. My prediction and the estimates from Zhang, Deschenes, Meng and Zhang (2018) are shown in Figure A-15. While I slightly overpredict sensitivity to cold and underpredict sensitivity to heat, my results are broadly consistent with their findings, lending external validity to my work.

However, when I estimate the response to temperature in my full sample of Chinese firms from 2003-2012, I produce the highly anomalous results shown in Figure A-16. This estimate using my full sample of Chinese data implies that extreme temperatures sharply and statistically significantly *increase* output, a finding inconsistent with my results from any other country in the world. Notably, this anomalous result begins to appear by including later years starting with 2008 in the regression, the same year Chen, Chen, Hsieh and Song (2019) start to find discrepancies in the data. They state that "local statistics increasingly misrepresent the true numbers after 2008" and "the micro-data of the ASIF [have] overstated aggregate output."

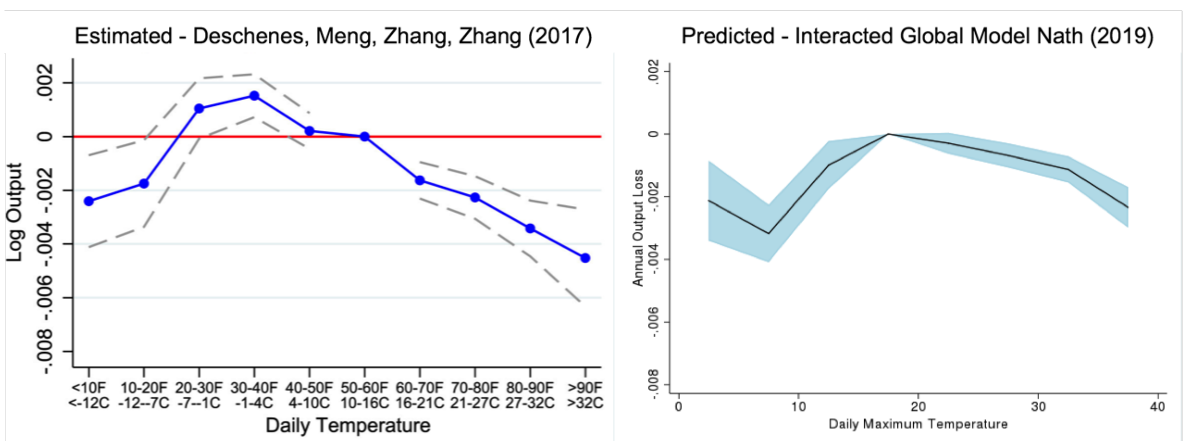
A somewhat puzzling fact is that my results suggest that this documented manipulation of data in China is systematically correlated with temperature. One plausible hypothesis is that Chinese provincial officials inflate reported manufacturing output to meet GDP targets in response to declines in other sectors more susceptible to temperature, such as agriculture. These targets have historically played a central role in the evaluation and promotion of government officials, and Lyu, Wang, Zhang and Zhang (2018) demonstrate that reported provincial GDP just barely hits target thresholds with implausible frequency. I cannot provide further evidence on the particular sources and methods of manipulation, but given the widespread external documentation of problems with this subset of the Chinese firm data and my very short panel that would remain when excluding these years in China, I exclude this dataset entirely from my main analysis. Still, I view the consistency of both my replication and predictions with the results of Zhang, Deschenes, Meng and Zhang (2018) as validating my central analysis.

Figure A-14: China Replication - Overlapping Years



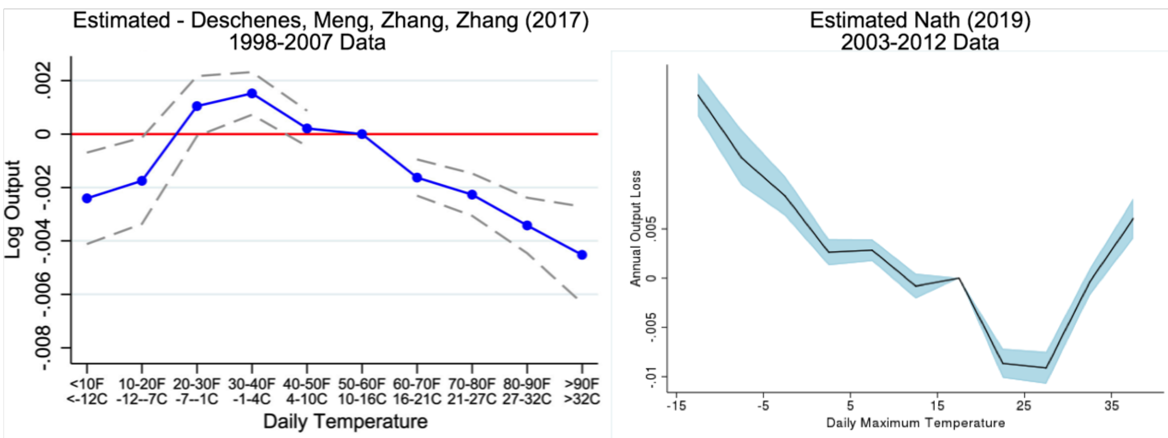
Notes: Left panel of the figure shows the effect of temperature on annual manufacturing output in China estimated by Zhang, Deschenes, Meng and Zhang (2018) using data from the Chinese Industrial Survey of the National Bureau of Statistics from 1998-2007. Right panel shows my replication of their result using data from the same dataset for 2003-2007 - the overlapping years of my data coverage. Temperature data is from GMFD.

Figure A-15: China Manufacturing Temperature Sensitivity - Estimated and Predicted



Notes: Left panel of the figure shows the effect of temperature on annual manufacturing output in China estimated by Zhang, Deschenes, Meng and Zhang (2018) using data from the Chinese Industrial Survey of the National Bureau of Statistics from 1998-2007. Right panel shows the predicted effect of temperature in China from evaluating my global interacted specification from Column 2 of Table 2 at China's income and average long-run temperature from 1998-2007. I do not use any data from China in my estimation or prediction.

Figure A-16: China Replication - Different Years



Notes: Left panel of the figure shows the effect of temperature on annual manufacturing output in China estimated by Zhang, Deschenes, Meng and Zhang (2018) using data from the Chinese Industrial Survey of the National Bureau of Statistics from 1998-2007. Right panel shows my replication of their result using data from the same dataset for 2003-2012 - the years of my data coverage. Temperature data is from GMFD.

Appendix D: Adaptation Benefits and Costs

In this section I explain how I use revealed preference methods developed by Carleton et al. (2018) to infer the costs firms incur from reducing the sensitivity of their production to extreme temperatures. To build intuition start by considering a simple example of otherwise identical firms in two cities, Seattle and Houston. Houston is hotter than Seattle, but Seattle heats up over the course of the century such that its exposure to CDD in 2100 is that of Houston in 2020. Let β represent lost annual revenues from exposure to a cooling degree day, a function of the adaptation investments the firm chooses to make. The annual costs of extreme heat to a firm in Seattle are given by $CDD_{Seattle} * \beta_{Seattle}$. Since Seattle suffers little exposure to extreme heat, its firms choose a lower (more negative) β than firms in Houston, as I find in my empirical estimates. If Seattle firms had chosen the Houston β associated with greater expected exposure to heat, the marginal benefits they would obtain are as follows:

$$MB = CDD_{Seattle} * (\beta_{Houston} - \beta_{Seattle})$$

Given that Seattle firms do not choose $\beta_{Houston}$, we know that the marginal costs of this incremental reduction in temperature sensitivity must exceed the marginal benefits. By repeating this logic for the firm's estimated temperature sensitivity for every year of warming from $Seattle_{2020}$ to $Seattle_{2100}$, we can construct the full marginal cost curve for the Seattle firm's projected change in chosen β from 2020 to 2100:

$$TC = \sum_{t=2020}^{2099} MC_t = \sum_{t=2020}^{2099} CDD_t * (\beta_{t+1} - \beta_t) \tag{25}$$

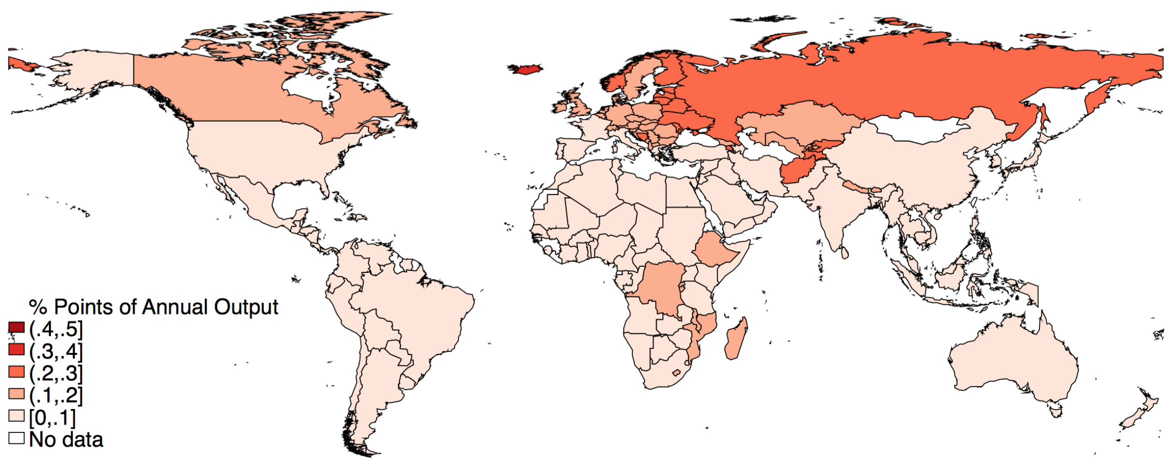
Note that the continuous version of Equation 25 also follows straight from the firm's first-order condition in the framework in Section 3.1. The firm's lost revenues from extreme heat are $CDD * \beta$ so the marginal benefit the firm receives from a reduction in β is given by CDD. Since the firm's optimal choice of β equates marginal benefit to marginal cost, we have marginal cost $c_\beta = CDD$ for the full range of CDDs.

The total benefits of future adaptation for firms in Seattle are given by the change in damages from choosing their optimal level of adaptation for expected heat exposure in 2100 rather than remaining at the adaptation level they choose in 2020:

$$TB = CDD_{2100} * (\beta_{2100} - \beta_{2020}) \tag{26}$$

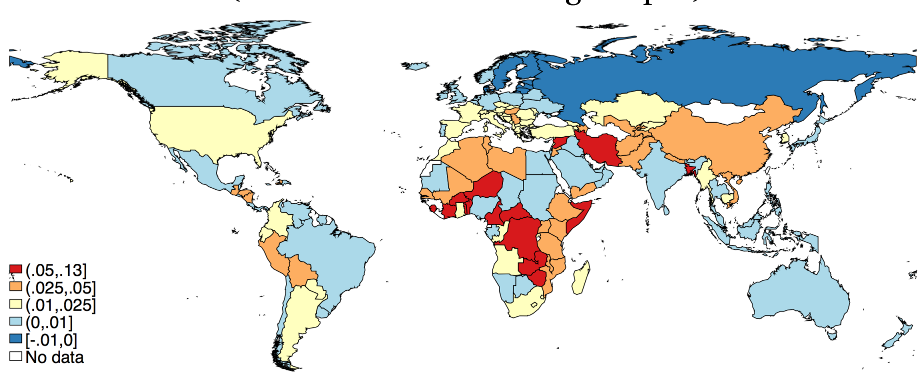
Because CDDs are increasing as countries become hotter, the benefits of adaptation in Equation 26 exceed the costs in Equation 25. Figure A-17 shows predicted manufacturing sensitivity to a hot day at end-of-century temperatures, which is substantially muted relative to the sensitivities at current temperatures shown in Figure 5. Figure A-18 show the costs of achieving this reduced sensitivity, as calculated using Equation 25, and Figure A-19 show the net benefits of firms adapting to changes in expected exposure to extreme heat.

Figure A-17: Predicted Effect of a 40°C Day on
Annual Manufacturing Revenue per Worker
At 2080 Average Temperatures



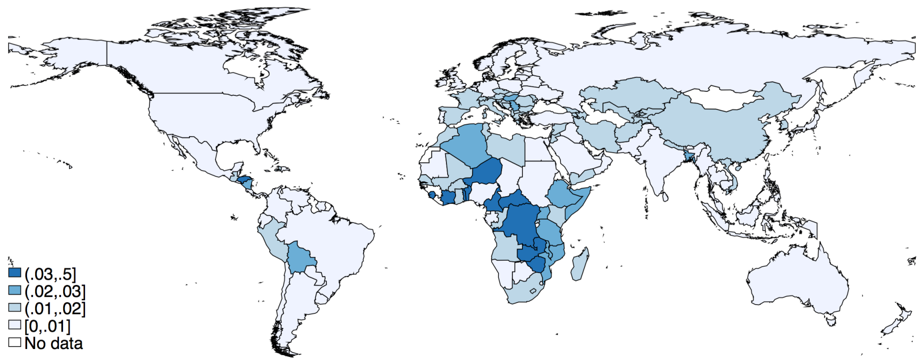
Notes: Map shows the predicted annual percentage point loss in revenue per worker from a 40°C day obtained by evaluating the interaction regression in Column 2 of Table 2 at each country's level of income and end-of-century long-run average temperature. Temperature sensitivities are lower in this figure than in Figure 5 because my results predict that firms will adapt to hot temperatures as the world warms.

Figure A-18: Firm-Level Adaptation Costs
(Share of Manufacturing Output)



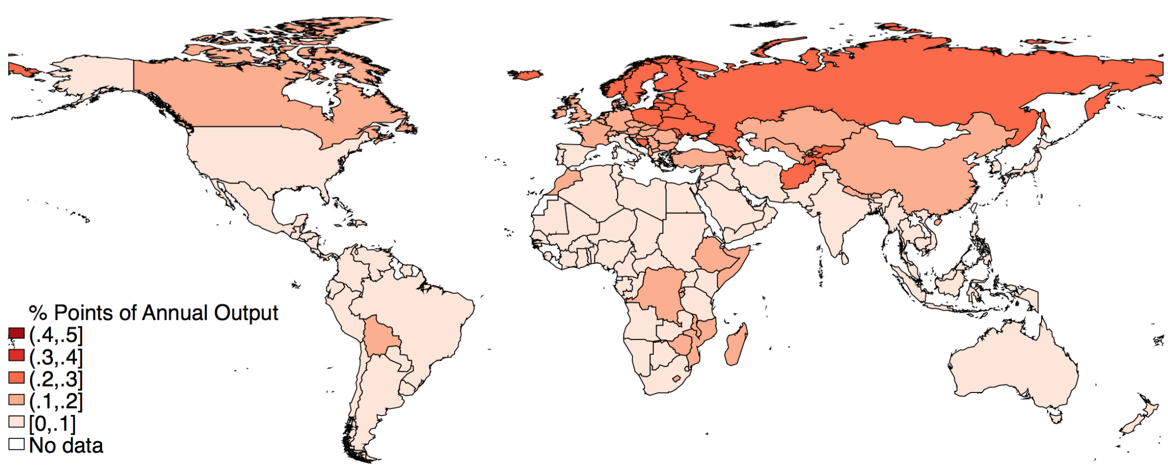
Notes: Map shows my calculations of the costs firms pay to achieve the lower temperature sensitivity shown in Appendix Figure A-17 compared to Figure 5. I infer these costs using a revealed preference approach developed by Carleton et al. (2018) that infers adaptation costs from the foregone benefits firms would have attained by reducing their heat sensitivity. The procedure is detailed in Appendix D.

Figure A-19: Firm-Level Adaptation Net Benefits
(Share of Manufacturing Output)



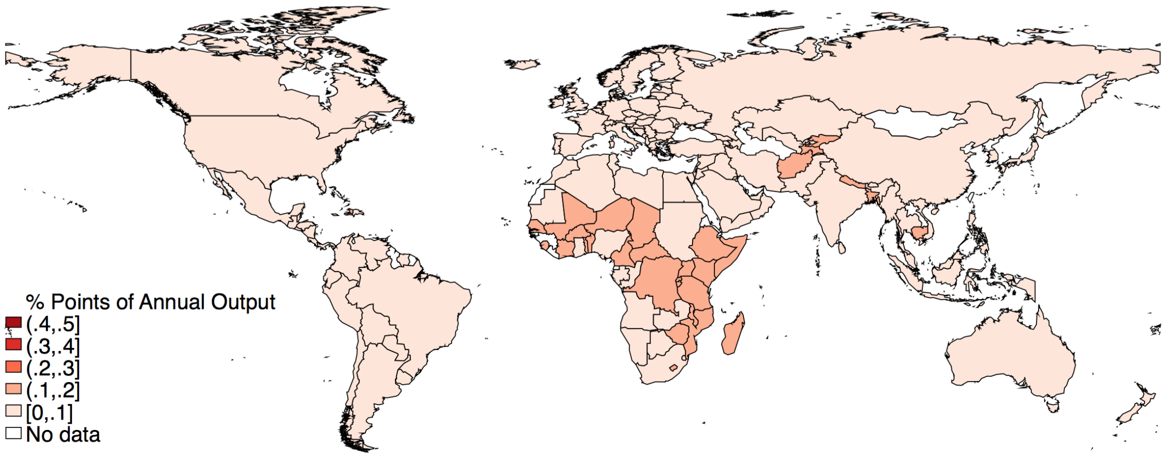
Notes: Map shows my calculations of the net benefits firms receive by investing to reduce their heat sensitivity as the climate warms. The benefits come from reducing heat sensitivity to the level shown in Appendix Figure A-17 compared to the original level in Figure 5. The inferred costs are shown in Appendix Figure A-18. The procedure to calculate these costs and benefits is detailed in Appendix D.

Figure A-20: Predicted Effect of a 40°C Day on Annual Services
Revenue per Worker



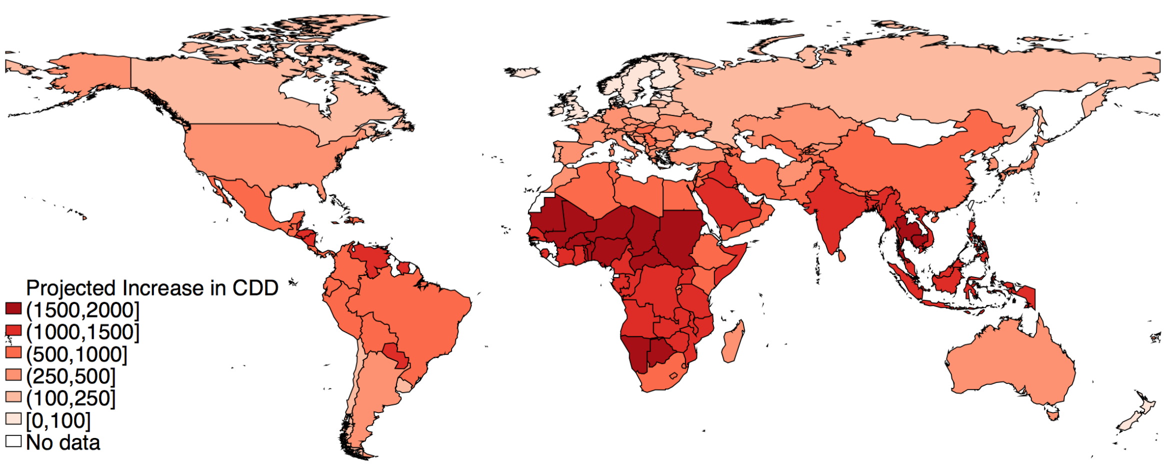
Notes: Map shows the predicted annual percentage point loss in revenue per worker from a 40°C day obtained by evaluating the interaction regression for a pooled sample of manufacturing and services firms in Column 5 of Table 2 at each country's level of income and long-run average temperature.

Figure A-21: Predicted Effect of a -5°C Day on Annual Services Revenue per Worker



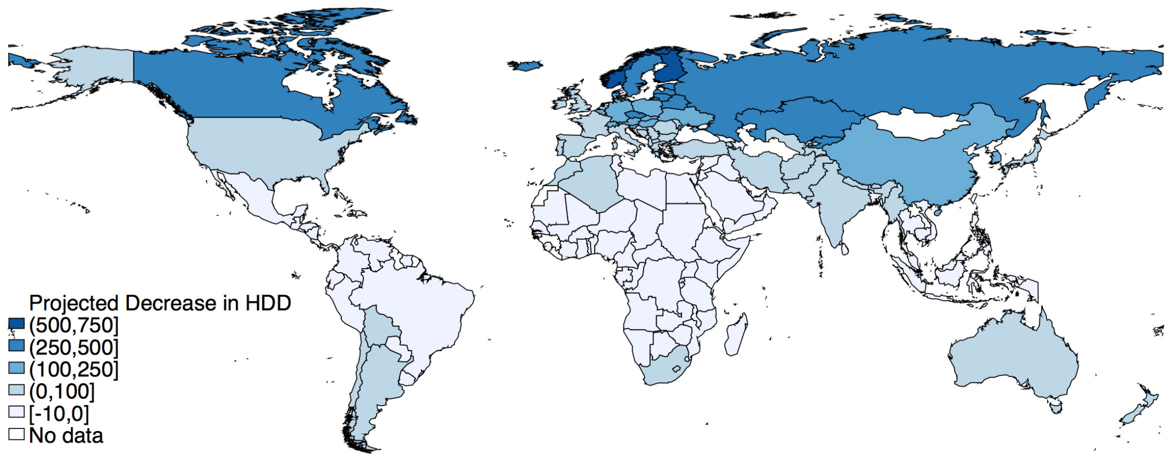
Notes: Map shows the predicted annual percentage point loss in revenue per worker from a -5°C day obtained by evaluating the interaction regression for a pooled sample of manufacturing and services firms in Column 5 of Table 2 at each country's level of income and long-run average temperature.

Figure A-22: Projected Change in Exposure to Extreme Heat



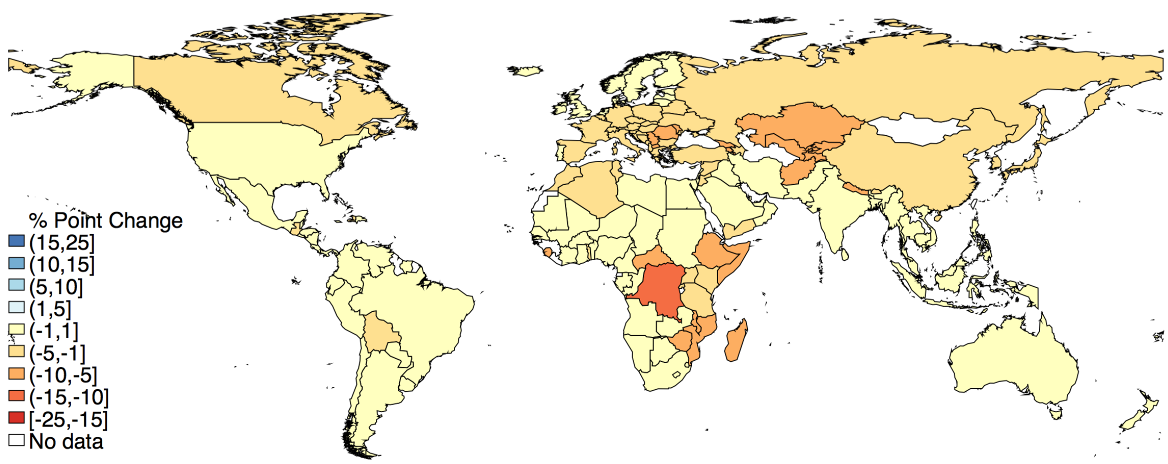
Notes: Map shows projections from the CSIRO-MK-3.6.0 global climate model of changes in exposure to extreme heat as measured by cooling degree days above 30°C between 2015 and the two decade average from 2080 to 2099.

Figure A-23: Projected Change in Exposure to Extreme Cold



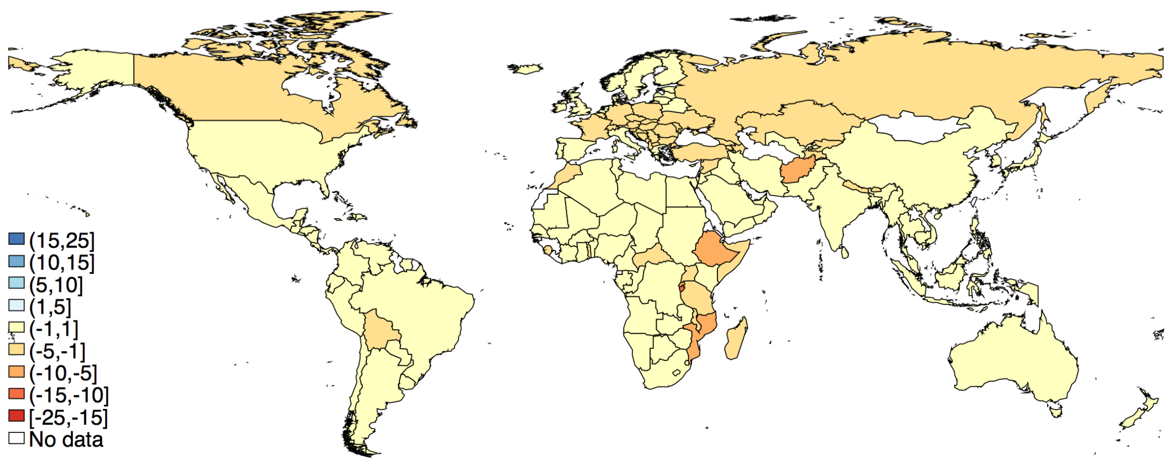
Notes: Map shows projections from the CSIRO-MK-3.6.0 global climate model of changes in exposure to extreme cold as measured by heating degree days below 5°C between 2015 and the two decade average from 2080 to 2099.

Figure A-24: Projected Impact of Climate Change on Services Productivity



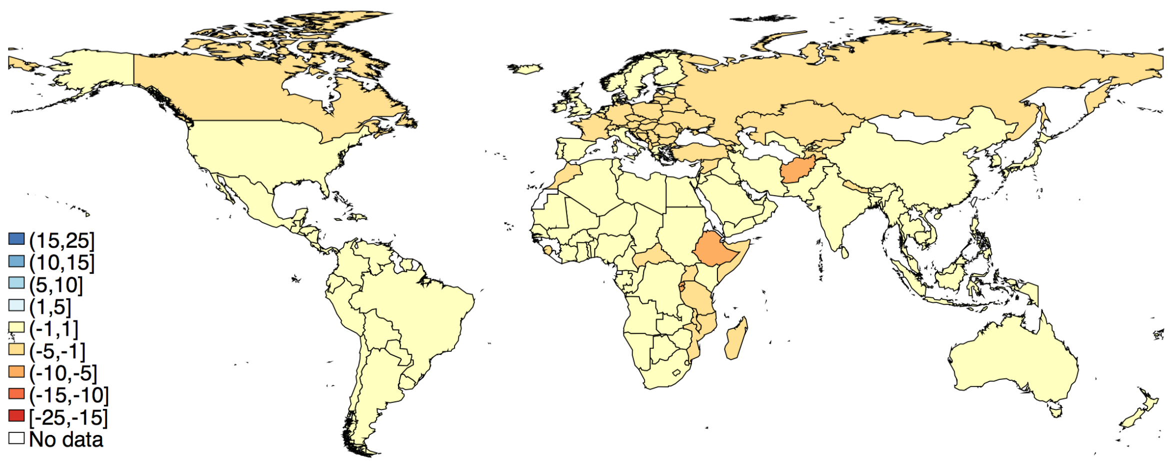
Notes: Map shows the projected impact of climate change on services productivity in 2080-2099 obtained by multiplying predicted temperature sensitivities by CSIRO-MK-3.6.0 global climate model predictions of changes in exposure to extreme heat and cold. Temperature sensitivities are calculated by evaluating the interaction regression from Column 5 of Table 2 at each country's income and end-of-century long-run average temperature.

Figure A-25: Projected Impact of Climate Change on Manufacturing Productivity Accounting for Economic Growth and Adaptation



Notes: Map shows the projected impact of climate change on manufacturing productivity in 2080-2099 obtained by multiplying predicted temperature sensitivities by CSIRO-MK-3.6.0 global climate model predictions of changes in exposure to extreme heat and cold. Temperature sensitivities are calculated by evaluating the interaction regression from Column 2 of Table 2 at each country's end-of-century long-run average temperature and 2080 income as projected by Cuaresma (2017). These estimates that account for economic growth show reduced losses relative to those in Figure 9 because my empirical results suggest that firms in richer countries have reduced exposure to extreme temperatures.

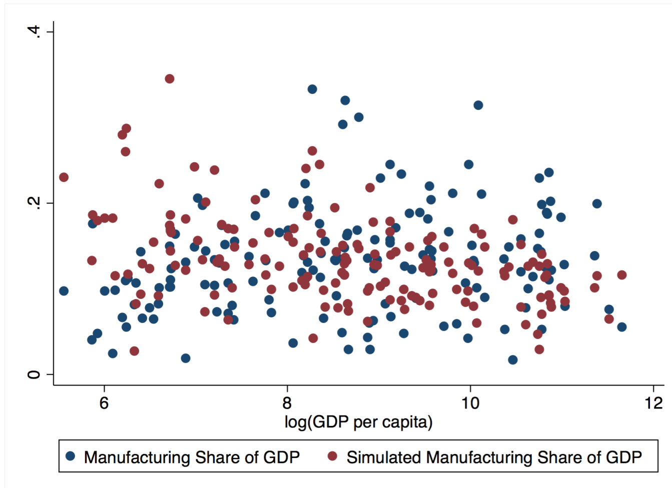
Figure A-26: Projected Impact of Climate Change on Services Productivity Accounting for Economic Growth and Adaptation



Notes: Map shows the projected impact of climate change on services productivity in 2080-2099 obtained by multiplying predicted temperature sensitivities by CSIRO-MK-3.6.0 global climate model predictions of changes in exposure to extreme heat and cold. Temperature sensitivities are calculated by evaluating the interaction regression from Column 5 of Table 2 at each country's end-of-century long-run average temperature and 2080 income as projected by Cuaresma (2017). These estimates that account for economic growth show reduced losses relative to those in Appendix Figure A-24 because my empirical estimates suggest that firms in richer countries have reduced exposure to extreme temperatures.

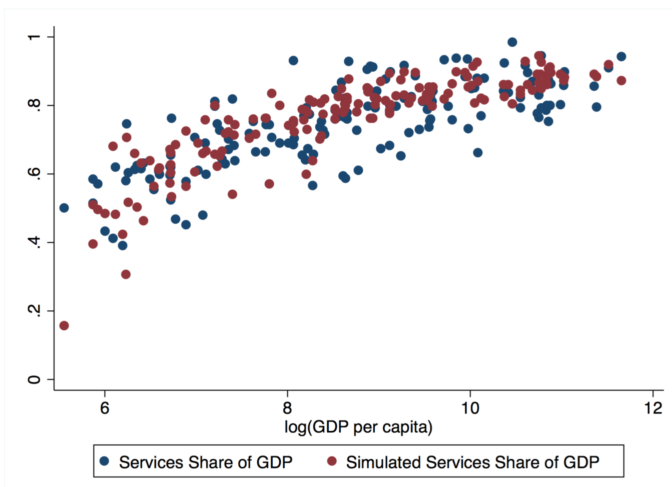
Appendix E: Additional Model Fit Figures

Figure A-27: Manufacturing Share of GDP - Data vs. Simulation



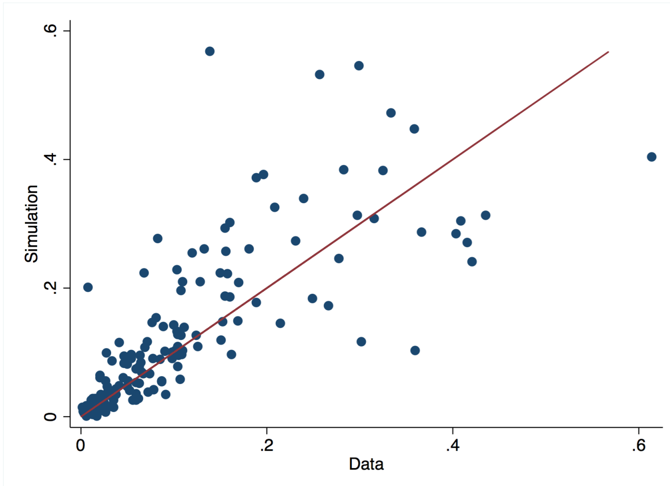
Notes: Graph shows the fit of simulated manufacturing share of GDP in the model to data from the World Bank.

Figure A-28: Services Share of GDP - Data vs. Simulation



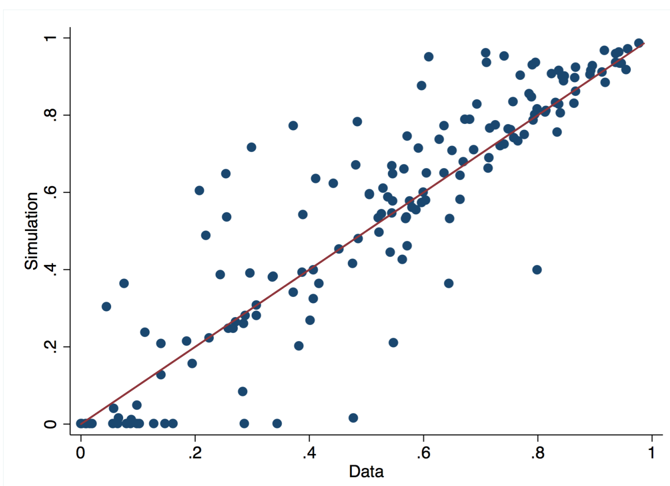
Notes: Graph shows the fit of simulated services share of GDP in the model to data from the World Bank.

Figure A-29: Agriculture Share of GDP - Data vs. Simulation



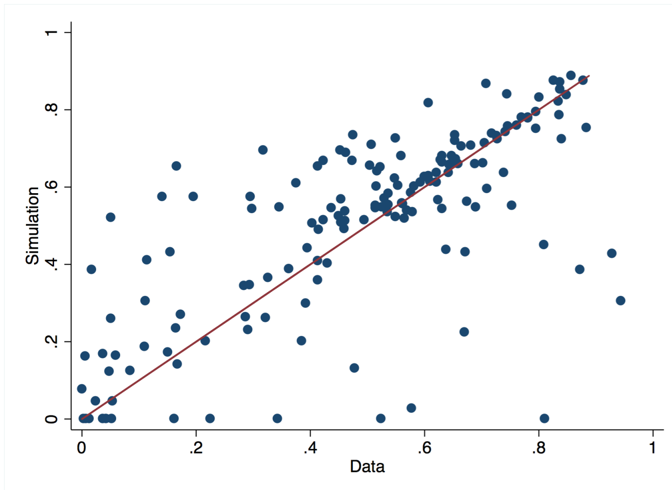
Notes: Graph shows another view of the fit of simulated agriculture share of GDP in the model to data from the World Bank also shown in Figure 7. A perfect fit would have all data points be on the 45°line where the simulated and actual values are equal. The simulation explains over 60% of the variation in the agriculture share of GDP.

Figure A-30: Domestic Production Share of Agriculture Expenditures - Data vs. Simulation



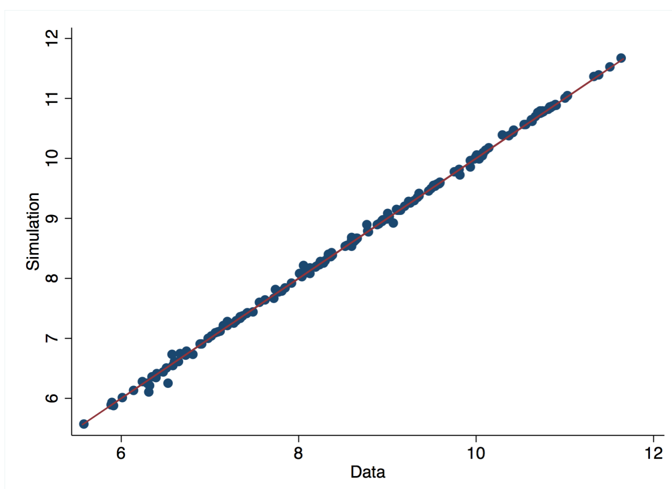
Notes: Graph shows the fit of simulated domestic production share of agricultural consumption in the model to data from Comtrade. As shown in Section 5.2, openness to food imports is a crucial parameter governing the response of labor reallocation to climate change. The simulation explains over 80% of the variation in the data for this moment.

Figure A-31: Manufacturing Domestic Production Share of Expenditures - Data vs. Simulation



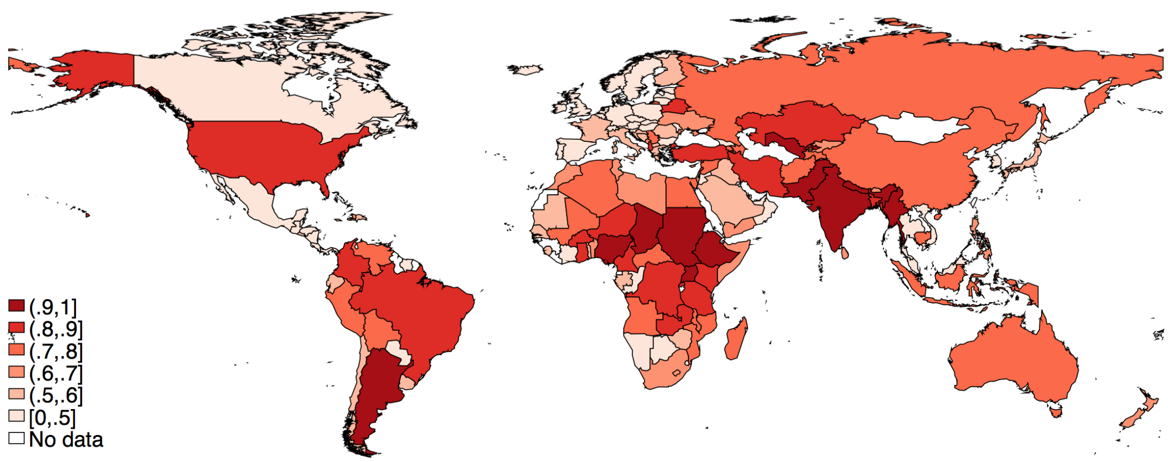
Notes: Graph shows the fit of simulated domestic production share of manufacturing consumption in the model to data from Comtrade.

Figure A-32: Log GDP Per Capita - Data vs. Simulation



Notes: Graph shows the fit of simulated domestic production share of manufacturing consumption in the model to data from the World Bank.

Figure A-33: Domestic Production Share of Expenditures in Agriculture - Model Simulation



Notes: Figure shows that the share of expenditures on domestically produced goods in agriculture is very high in many developing countries with high barriers to trade. Table 5 shows that these simulated values track closely to the data.

Appendix F: Country-by-Country Model Counterfactual Results

Table A-3: Counterfactual Ag Net Export Share of GDP - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Angola	-.258	0	-.01	-.019
Benin	-.327	0	-.028	-.074
Botswana	-.469	0	-.096	-.176
Burkina Faso	-.243	0	-.003	-.055
Cameroon	-.2	-.005	-.026	-.052
Cape Verde	-.327	-.012	-.107	-.222
Central African Republic	-.601	-.076	-.097	-.385
Chad	-.601	0	.038	-.121
Comoros	-.217	-.075	-.156	-.204
Congo	-.601	0	-.104	-.241
Cote d'Ivoire	-.143	0	.005	0
Democratic Republic of Congo	-.147	-.142	-.045	.002
Ethiopia	-.313	-.102	.052	.026
Gabon	-.601	0	-.056	-.162
Gambia	-.327	0	-.161	-.216
Ghana	-.14	0	.059	.057
Kenya	-.054	-.044	.027	.051
Lesotho	-.469	-.055	-.05	-.172
Madagascar	-.262	-.067	.006	-.034

Table A-4: Counterfactual Ag Net Export Share of GDP - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Malawi	-.313	-.111	-.052	-.041
Mali	-.356	0	-.043	-.106
Mauritania	-.327	0	-.05	-.144
Mauritius	-.262	0	-.002	-.03
Mozambique	-.217	-.104	-.037	-.015
Namibia	-.469	0	-.005	-.097
Niger	-.341	0	-.041	-.174
Nigeria	-.185	0	.006	.005
Rwanda	-.601	-.058	0	-.289
Senegal	-.519	0	-.025	-.182
Seychelles	-.262	0	-.029	-.03
Sierra Leone	-.327	-.071	-.086	-.053
Somalia	-.166	-.125	-.048	-.04
South Africa	-.334	0	.006	-.011
Sudan	-.561	0	.022	-.066
Swaziland	-.469	-.006	-.132	-.258
Tanzania	-.242	-.057	.001	-.03
Togo	-.327	-.042	.13	.075
Uganda	-.168	-.057	.032	.009
Zambia	-.396	0	-.023	-.101
Zimbabwe	-.379	-.099	-.06	-.15

Table A-5: Counterfactual Ag Net Export Share of GDP - Middle East and North Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Algeria	-.36	-.019	-.004	-.024
Bahrain	-.219	0	-.015	-.014
Egypt	.113	0	-.002	.024
Iran	-.289	.002	-.001	-.009
Iraq	-.411	0	-.018	-.057
Jordan	-.27	-.019	-.009	-.009
Kuwait	-.219	0	-.022	-.028
Lebanon	-.27	-.012	.061	.047
Libya	-.124	0	.006	-.001
Morocco	-.39	-.038	0	-.054
Oman	-.219	0	-.005	-.012
Qatar	-.219	0	-.003	-.004
Saudi Arabia	-.219	0	-.008	-.013
Syria	-.27	-.049	-.013	-.038
Tunisia	-.36	-.019	-.003	-.038
United Arab Emirates	-.219	0	.003	.005
Yemen	-.282	-.031	-.019	-.037

Table A-6: Counterfactual Ag Net Export Share of GDP - Asia

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Afghanistan	-.247	-.086	-.001	-.011
Azerbaijan	-.226	-.044	-.021	-.032
Bangladesh	-.217	-.016	-.03	-.044
Bhutan	-.381	-.034	-.112	-.243
Brunei	-.179	0	.006	-.002
Cambodia	-.271	0	-.022	-.066
China	-.072	-.036	-.021	-.017
Hong Kong	-.072	0	-.002	0
India	-.381	0	0	-.026
Japan	-.057	-.01	-.01	-.01
Kazakhstan	.114	-.031	-.005	.005
Kyrgyzstan	-.059	-.039	-.019	-.025
Maldives	-.201	0	-.033	-.024
Myanmar	-.393	0	.012	-.007
Nepal	-.173	-.07	0	.01
Pakistan	-.304	.001	.016	0
Philippines	-.234	0	-.033	-.059
South Korea	-.093	-.015	-.024	-.025
Sri Lanka	-.201	0	-.01	-.002
Tajikistan	-.059	-.097	-.053	-.06
Thailand	-.262	0	-.041	-.071
Uzbekistan	-.121	-.065	.028	.053
Vietnam	-.151	0	-.014	-.037

Table A-7: Counterfactual Ag Net Export Share of GDP - South America

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Argentina	-.111	0	.05	.053
Barbados	-.237	0	.013	.026
Bolivia	-.43	-.042	-.006	-.064
Brazil	-.169	0	.011	.009
Chile	-.244	-.009	.005	-.012
Colombia	-.232	0	.009	.002
Ecuador	-.288	0	.019	-.001
Honduras	-.237	-.006	-.062	-.1
Paraguay	-.43	0	.061	-.049
Peru	-.306	-.005	.006	-.024
Suriname	-.43	0	-.009	-.036
Trinidad and Tobago	-.237	0	-.042	-.039
Uruguay	-.43	-.008	.046	-.012
Venezuela	-.319	0	-.005	-.014

Table A-8: Counterfactual Ag Net Export Share of GDP - North and Central America

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Bahamas	-.237	0	-.008	-.022
Belize	-.237	0	.027	.014
Canada	-.022	-.007	.005	.012
Costa Rica	-.237	0	-.02	-.028
Dominican Republic	-.237	0	-.016	-.03
El Salvador	-.237	0	.027	-.019
Guatemala	-.237	-.017	.045	.021
Haiti	-.237	-.045	-.089	-.091
Jamaica	-.237	0	-.011	-.029
Mexico	-.354	0	-.029	-.055
Nicaragua	-.237	0	-.032	-.081
Panama	-.237	0	-.003	-.017
United States	-.059	.003	.012	.016

Table A-9: Counterfactual Ag Net Export Share of GDP - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Albania	-.086	-.053	.039	.033
Armenia	-.226	-.089	-.015	-.033
Austria	-.05	-.029	-.009	-.006
Belarus	.031	.012	0	.006
Belgium	-.067	-.015	.005	.005
Bosnia and Herzegovina	-.086	-.052	-.02	-.013
Bulgaria	-.086	-.054	.022	.028
Croatia	-.05	-.044	.001	.014
Cyprus	-.078	0	.045	.038
Czech Republic	-.05	-.021	-.009	-.009
Denmark	.109	.006	.019	.038
Estonia	.031	.033	.008	.028
Finland	.109	.02	-.006	-.001
France	-.067	-.027	.014	.02
Georgia	-.226	-.091	-.065	-.108
Germany	-.029	-.021	-.005	-.002
Greece	-.078	-.012	.011	.015
Hungary	-.05	-.05	-.002	.005
Iceland	.109	.009	.049	.073
Ireland	-.039	0	-.017	-.015
Israel	-.27	0	.002	-.005
Italy	-.074	-.018	.003	.005

Table A-10: Counterfactual Ag Net Export Share of GDP - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Latvia	.031	.032	.002	.031
Lithuania	.031	.018	-.001	.016
Luxembourg	-.05	-.018	.001	.006
Macedonia	-.086	-.061	.042	.046
Malta	-.074	0	-.011	.003
Moldova	-.086	-.07	.057	-.012
Montenegro	-.086	-.03	.018	.026
Netherlands	-.07	-.007	.013	.015
Norway	.109	-.006	.009	.018
Poland	-.047	-.01	-.019	-.018
Portugal	-.096	-.009	-.006	-.005
Romania	-.066	-.056	-.03	-.022
Russia	-.077	-.006	0	.001
Serbia	-.086	-.075	.004	.011
Slovakia	-.05	-.032	-.005	-.005
Slovenia	-.05	-.039	-.025	-.024
Spain	-.089	-.012	.006	.006
Sweden	.109	.011	-.005	.001
Switzerland	-.05	-.031	-.013	-.012
Turkey	-.162	-.038	.004	.007
Ukraine	-.052	-.038	.012	.035
United Kingdom	-.039	-.002	.002	.007

Table A-11: Counterfactual Ag Net Export Share of GDP - Western Pacific and Oceania

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Australia	-.266	0	.024	.013
Fiji	.022	-.004	-.01	.044
Indonesia	-.179	0	-.007	-.009
Malaysia	-.225	0	-.005	-.009
New Zealand	.022	0	.062	.077
Singapore	-.225	0	-.014	-.016

Table A-12: Counterfactual Ag Domestic Expenditure Shares - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Angola	-.258	0	.777	.684
Benin	-.327	0	.636	.462
Botswana	-.469	0	.338	.178
Burkina Faso	-.243	0	.825	.754
Cameroon	-.2	-.005	.815	.753
Cape Verde	-.327	-.012	.542	.197
Central African Republic	-.601	-.076	.709	.323
Chad	-.601	0	.978	.681
Comoros	-.217	-.075	.299	.236
Congo	-.601	0	.408	.041
Cote d'Ivoire	-.143	0	.308	.297
Democratic Republic of Congo	-.147	-.142	.866	.887
Ethiopia	-.313	-.102	.958	.929
Gabon	-.601	0	.567	.098
Gambia	-.327	0	.046	.074
Ghana	-.14	0	.814	.787
Kenya	-.054	-.044	.867	.906
Lesotho	-.469	-.055	.271	.084
Madagascar	-.262	-.067	.786	.738

Table A-13: Counterfactual Ag Domestic Expenditure Shares - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Malawi	-.313	-.111	.791	.779
Mali	-.356	0	.797	.654
Mauritania	-.327	0	.527	.376
Mauritius	-.262	0	.129	.074
Mozambique	-.217	-.104	.758	.792
Namibia	-.469	0	.259	.1
Niger	-.341	0	.843	.598
Nigeria	-.185	0	.944	.925
Rwanda	-.601	-.058	.848	.538
Senegal	-.519	0	.571	.139
Seychelles	-.262	0	.001	.001
Sierra Leone	-.327	-.071	.598	.733
Somalia	-.166	-.125	.673	.695
South Africa	-.334	0	.67	.472
Sudan	-.561	0	.914	.573
Swaziland	-.469	-.006	.336	.172
Tanzania	-.242	-.057	.867	.827
Togo	-.327	-.042	.522	.521
Uganda	-.168	-.057	.918	.885
Zambia	-.396	0	.838	.756
Zimbabwe	-.379	-.099	.563	.498

Table A-14: Counterfactual Ag Domestic Expenditure Shares - Middle East and North Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Algeria	-.36	-.019	.713	.444
Bahrain	-.219	0	.104	.084
Egypt	.113	0	.735	.821
Iran	-.289	.002	.864	.794
Iraq	-.411	0	.545	.332
Jordan	-.27	-.019	.402	.286
Kuwait	-.219	0	.141	.117
Lebanon	-.27	-.012	.8	.655
Libya	-.124	0	.601	.615
Morocco	-.39	-.038	.689	.452
Oman	-.219	0	.098	.071
Qatar	-.219	0	.581	.501
Saudi Arabia	-.219	0	.521	.43
Syria	-.27	-.049	.715	.598
Tunisia	-.36	-.019	.604	.324
United Arab Emirates	-.219	0	.287	.22
Yemen	-.282	-.031	.664	.589

Table A-15: Counterfactual Ag Domestic Expenditure Shares - Asia

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Afghanistan	-.247	-.086	.742	.77
Azerbaijan	-.226	-.044	.748	.68
Bangladesh	-.217	-.016	.832	.802
Bhutan	-.381	-.034	.61	.439
Brunei	-.179	0	.407	.413
Cambodia	-.271	0	.795	.664
China	-.072	-.036	.711	.757
Hong Kong	-.072	0	.345	.366
India	-.381	0	.943	.862
Japan	-.057	-.01	.506	.553
Kazakhstan	.114	-.031	.892	.942
Kyrgyzstan	-.059	-.039	.694	.622
Maldives	-.201	0	.112	.11
Myanmar	-.393	0	.937	.887
Nepal	-.173	-.07	.937	.948
Pakistan	-.304	.001	.946	.89
Philippines	-.234	0	.636	.558
South Korea	-.093	-.015	.254	.268
Sri Lanka	-.201	0	.65	.68
Tajikistan	-.059	-.097	.799	.782
Thailand	-.262	0	.373	.264
Uzbekistan	-.121	-.065	.956	.95
Vietnam	-.151	0	.482	.483

Table A-16: Counterfactual Ag Domestic Expenditure Shares - South America

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Argentina	-.111	0	.919	.925
Barbados	-.237	0	.058	.068
Bolivia	-.43	-.042	.758	.512
Brazil	-.169	0	.896	.883
Chile	-.244	-.009	.506	.4
Colombia	-.232	0	.837	.806
Ecuador	-.288	0	.539	.503
Honduras	-.237	-.006	.219	.163
Paraguay	-.43	0	.485	.195
Peru	-.306	-.005	.717	.628
Suriname	-.43	0	.413	.074
Trinidad and Tobago	-.237	0	.016	.01
Uruguay	-.43	-.008	.592	.288
Venezuela	-.319	0	.793	.63

Table A-17: Counterfactual Ag Domestic Expenditure Shares - North and Central America

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Bahamas	-.237	0	.245	.122
Belize	-.237	0	.077	.061
Canada	-.022	-.007	.268	.32
Costa Rica	-.237	0	.01	.005
Dominican Republic	-.237	0	.547	.455
El Salvador	-.237	0	.546	.41
Guatemala	-.237	-.017	.487	.425
Haiti	-.237	-.045	.628	.593
Jamaica	-.237	0	.57	.541
Mexico	-.354	0	.442	.182
Nicaragua	-.237	0	.255	.194
Panama	-.237	0	.477	.359
United States	-.059	.003	.835	.853

Table A-18: Counterfactual Ag Domestic Expenditure Shares - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Albania	-.086	-.053	.84	.814
Armenia	-.226	-.089	.79	.662
Austria	-.05	-.029	.088	.094
Belarus	.031	.012	.846	.862
Belgium	-.067	-.015	.099	.093
Bosnia and Herzegovina	-.086	-.052	.53	.526
Bulgaria	-.086	-.054	.382	.383
Croatia	-.05	-.044	.576	.639
Cyprus	-.078	0	.644	.611
Czech Republic	-.05	-.021	.141	.148
Denmark	.109	.006	.163	.214
Estonia	.031	.033	.372	.405
Finland	.109	.02	.545	.678
France	-.067	-.027	.549	.581
Georgia	-.226	-.091	.39	.294
Germany	-.029	-.021	.147	.178
Greece	-.078	-.012	.588	.585
Hungary	-.05	-.05	.225	.236
Iceland	.109	.009	.057	.069
Ireland	-.039	0	.002	.002
Israel	-.27	0	.664	.457
Italy	-.074	-.018	.571	.592

Table A-19: Counterfactual Ag Domestic Expenditure Shares - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Latvia	.031	.032	.284	.29
Lithuania	.031	.018	.081	.089
Luxembourg	-.05	-.018	.065	.085
Macedonia	-.086	-.061	.598	.611
Malta	-.074	0	.067	.073
Moldova	-.086	-.07	.452	.392
Montenegro	-.086	-.03	.646	.659
Netherlands	-.07	-.007	.088	.091
Norway	.109	-.006	.285	.354
Poland	-.047	-.01	.308	.302
Portugal	-.096	-.009	.196	.185
Romania	-.066	-.056	.572	.625
Russia	-.077	-.006	.753	.764
Serbia	-.086	-.075	.726	.745
Slovakia	-.05	-.032	.288	.289
Slovenia	-.05	-.039	.186	.195
Spain	-.089	-.012	.418	.422
Sweden	.109	.011	.298	.421
Switzerland	-.05	-.031	.021	.025
Turkey	-.162	-.038	.894	.88
Ukraine	-.052	-.038	.681	.689
United Kingdom	-.039	-.002	.478	.531

Table A-20: Counterfactual Ag Domestic Expenditure Shares - Western Pacific and Oceania

Country	Ag Productivity Change	Manufacturing Productivity Change	Baseline	Counterfactual
Australia	-.266	0	.766	.617
Fiji	.022	-.004	.388	.528
Indonesia	-.179	0	.77	.732
Malaysia	-.225	0	.208	.175
New Zealand	.022	0	.606	.69
Singapore	-.225	0	.01	.008

Table A-21: Counterfactual Ag GDP Shares - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Angola	-.258	0	.05	.065	.055
Benin	-.327	0	.156	.213	.154
Botswana	-.469	0	.062	.149	.044
Burkina Faso	-.243	0	.24	.289	.233
Cameroon	-.2	-.005	.216	.254	.226
Cape Verde	-.327	-.012	.163	.242	.076
Central African Republic	-.601	-.076	.299	.562	.21
Chad	-.601	0	.257	.438	.258
Comoros	-.217	-.075	.083	.123	.067
Congo	-.601	0	.092	.257	.011
Cote d'Ivoire	-.143	0	.17	.188	.183
Democratic Republic of Congo	-.147	-.142	.421	.457	.506
Ethiopia	-.313	-.102	.359	.437	.409
Gabon	-.601	0	.073	.187	.018
Gambia	-.327	0	.008	.06	.021
Ghana	-.14	0	.181	.195	.193
Kenya	-.054	-.044	.156	.16	.185
Lesotho	-.469	-.055	.107	.191	.028
Madagascar	-.262	-.067	.404	.481	.436

Table A-22: Counterfactual Ag GDP Shares - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Malawi	-.313	-.111	.436	.54	.55
Mali	-.356	0	.197	.278	.205
Mauritania	-.327	0	.249	.336	.224
Mauritius	-.262	0	.038	.048	.016
Mozambique	-.217	-.104	.367	.426	.451
Namibia	-.469	0	.099	.157	.04
Niger	-.341	0	.325	.432	.277
Nigeria	-.185	0	.068	.078	.077
Rwanda	-.601	-.058	.409	.678	.351
Senegal	-.519	0	.153	.267	.05
Seychelles	-.262	0	.016	.026	.025
Sierra Leone	-.327	-.071	.139	.204	.246
Somalia	-.166	-.125	.334	.373	.382
South Africa	-.334	0	.056	.073	.052
Sudan	-.561	0	.12	.197	.095
Swaziland	-.469	-.006	.102	.224	.062
Tanzania	-.242	-.057	.298	.354	.321
Togo	-.327	-.042	.316	.372	.316
Uganda	-.168	-.057	.416	.459	.433
Zambia	-.396	0	.36	.496	.41
Zimbabwe	-.379	-.099	.302	.419	.322

Table A-23: Counterfactual Ag GDP Shares - Middle East and North Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Algeria	-.36	-.019	.034	.049	.025
Bahrain	-.219	0	.015	.021	.02
Egypt	.113	0	.077	.071	.098
Iran	-.289	.002	.051	.065	.057
Iraq	-.411	0	.05	.081	.034
Jordan	-.27	-.019	.038	.05	.046
Kuwait	-.219	0	.005	.011	.005
Lebanon	-.27	-.012	.079	.083	.068
Libya	-.124	0	.067	.073	.066
Morocco	-.39	-.038	.1	.141	.077
Oman	-.219	0	.023	.029	.02
Qatar	-.219	0	.008	.011	.009
Saudi Arabia	-.219	0	.016	.021	.016
Syria	-.27	-.049	.09	.114	.084
Tunisia	-.36	-.019	.055	.076	.033
United Arab Emirates	-.219	0	.016	.018	.019
Yemen	-.282	-.031	.11	.142	.121

Table A-24: Counterfactual Ag GDP Shares - Asia

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Afghanistan	-.247	-.086	.278	.33	.321
Azerbaijan	-.226	-.044	.088	.108	.095
Bangladesh	-.217	-.016	.189	.228	.212
Bhutan	-.381	-.034	.267	.392	.239
Brunei	-.179	0	.027	.03	.022
Cambodia	-.271	0	.19	.24	.189
China	-.072	-.036	.064	.068	.074
Hong Kong	-.072	0	.018	.019	.021
India	-.381	0	.161	.224	.194
Japan	-.057	-.01	.012	.013	.014
Kazakhstan	.114	-.031	.088	.08	.091
Kyrgyzstan	-.059	-.039	.156	.162	.152
Maldives	-.201	0	.021	.03	.039
Myanmar	-.393	0	.209	.288	.266
Nepal	-.173	-.07	.283	.317	.328
Pakistan	-.304	.001	.133	.167	.148
Philippines	-.234	0	.105	.133	.104
South Korea	-.093	-.015	.012	.014	.013
Sri Lanka	-.201	0	.109	.129	.137
Tajikistan	-.059	-.097	.232	.239	.233
Thailand	-.262	0	.072	.099	.061
Uzbekistan	-.121	-.065	.108	.115	.14
Vietnam	-.151	0	.158	.178	.155

Table A-25: Counterfactual Ag GDP Shares - South America

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Argentina	-.111	0	.065	.067	.07
Barbados	-.237	0	.035	.04	.054
Bolivia	-.43	-.042	.125	.186	.115
Brazil	-.169	0	.063	.071	.068
Chile	-.244	-.009	.053	.063	.045
Colombia	-.232	0	.066	.077	.07
Ecuador	-.288	0	.098	.12	.098
Honduras	-.237	-.006	.082	.111	.064
Paraguay	-.43	0	.151	.194	.065
Peru	-.306	-.005	.104	.133	.099
Suriname	-.43	0	.028	.046	.005
Trinidad and Tobago	-.237	0	.004	.014	.011
Uruguay	-.43	-.008	.091	.113	.048
Venezuela	-.319	0	.027	.037	.026

Table A-26: Counterfactual Ag GDP Shares - North and Central America

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Bahamas	-.237	0	.02	.025	.007
Belize	-.237	0	.104	.12	.104
Canada	-.022	-.007	.019	.019	.026
Costa Rica	-.237	0	.021	.03	.017
Dominican Republic	-.237	0	.046	.059	.043
El Salvador	-.237	0	.108	.126	.075
Guatemala	-.237	-.017	.151	.173	.146
Haiti	-.237	-.045	.161	.208	.203
Jamaica	-.237	0	.074	.092	.073
Mexico	-.354	0	.031	.052	.014
Nicaragua	-.237	0	.11	.139	.082
Panama	-.237	0	.06	.074	.056
United States	-.059	.003	.023	.024	.028

Table A-27: Counterfactual Ag GDP Shares - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Albania	-.086	-.053	.129	.134	.127
Armenia	-.226	-.089	.104	.126	.104
Austria	-.05	-.029	.012	.012	.015
Belarus	.031	.012	.05	.049	.056
Belgium	-.067	-.015	.02	.021	.02
Bosnia and Herzegovina	-.086	-.052	.047	.051	.057
Bulgaria	-.086	-.054	.06	.062	.068
Croatia	-.05	-.044	.042	.043	.058
Cyprus	-.078	0	.06	.061	.054
Czech Republic	-.05	-.021	.018	.019	.018
Denmark	.109	.006	.033	.032	.051
Estonia	.031	.033	.036	.036	.056
Finland	.109	.02	.013	.012	.017
France	-.067	-.027	.026	.027	.033
Georgia	-.226	-.091	.086	.113	.062
Germany	-.029	-.021	.011	.011	.015
Greece	-.078	-.012	.037	.038	.043
Hungary	-.05	-.05	.028	.029	.037
Iceland	.109	.009	.063	.062	.086
Ireland	-.039	0	.002	.003	.006
Israel	-.27	0	.016	.019	.011
Italy	-.074	-.018	.019	.019	.021

Table A-28: Counterfactual Ag GDP Shares - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Latvia	.031	.032	.037	.036	.064
Lithuania	.031	.018	.035	.034	.052
Luxembourg	-.05	-.018	.013	.014	.019
Macedonia	-.086	-.061	.104	.108	.112
Malta	-.074	0	.006	.007	.022
Moldova	-.086	-.07	.169	.175	.104
Montenegro	-.086	-.03	.054	.057	.065
Netherlands	-.07	-.007	.027	.028	.029
Norway	.109	-.006	.02	.019	.027
Poland	-.047	-.01	.031	.033	.034
Portugal	-.096	-.009	.026	.028	.029
Romania	-.066	-.056	.06	.063	.073
Russia	-.077	-.006	.03	.032	.033
Serbia	-.086	-.075	.069	.073	.08
Slovakia	-.05	-.032	.022	.023	.022
Slovenia	-.05	-.039	.017	.018	.019
Spain	-.089	-.012	.023	.024	.024
Sweden	.109	.011	.009	.008	.015
Switzerland	-.05	-.031	.003	.004	.005
Turkey	-.162	-.038	.047	.053	.055
Ukraine	-.052	-.038	.105	.108	.132
United Kingdom	-.039	-.002	.015	.015	.02

Table A-29: Counterfactual Ag GDP Shares - Western Pacific and Oceania

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Australia	-.266	0	.036	.039	.027
Fiji	.022	-.004	.126	.124	.185
Indonesia	-.179	0	.112	.129	.126
Malaysia	-.225	0	.042	.051	.045
New Zealand	.022	0	.078	.077	.093
Singapore	-.225	0	.007	.011	.007

Table A-30: Counterfactual GDP Losses (Share of GDP) - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Angola	-.258	0	-.018	-.027	-.025
Benin	-.327	0	-.07	-.101	-.084
Botswana	-.469	0	-.096	-.196	-.147
Burkina Faso	-.243	0	-.065	-.091	-.082
Cameroon	-.2	-.005	-.053	-.097	-.091
Cape Verde	-.327	-.012	-.108	-.216	-.077
Central African Republic	-.601	-.076	-.331	-.527	-.45
Chad	-.601	0	-.182	-.363	-.332
Comoros	-.217	-.075	-.102	-.112	-.047
Congo	-.601	0	-.165	-.323	-.121
Cote d'Ivoire	-.143	0	-.025	-.032	-.033
Democratic Republic of Congo	-.147	-.142	-.132	-.174	-.174
Ethiopia	-.313	-.102	-.163	-.218	-.217
Gabon	-.601	0	-.111	-.247	-.117
Gambia	-.327	0	-.065	-.063	-.096
Ghana	-.14	0	-.018	-.023	-.018
Kenya	-.054	-.044	-.037	-.038	-.034
Lesotho	-.469	-.055	-.131	-.18	-.109
Madagascar	-.262	-.067	-.144	-.209	-.2

Table A-31: Counterfactual GDP Losses (Share of GDP) - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Malawi	-.313	-.111	-.209	-.317	-.318
Mali	-.356	0	-.1	-.144	-.127
Mauritania	-.327	0	-.112	-.203	-.167
Mauritius	-.262	0	-.012	-.015	-.008
Mozambique	-.217	-.104	-.14	-.192	-.199
Namibia	-.469	0	-.064	-.11	-.063
Niger	-.341	0	-.142	-.231	-.177
Nigeria	-.185	0	-.013	-.015	-.015
Rwanda	-.601	-.058	-.334	-.557	-.508
Senegal	-.519	0	-.122	-.233	-.123
Seychelles	-.262	0	-.013	-.011	-.005
Sierra Leone	-.327	-.071	-.123	-.142	-.168
Somalia	-.166	-.125	-.126	-.151	-.15
South Africa	-.334	0	-.02	-.028	-.023
Sudan	-.561	0	-.078	-.144	-.125
Swaziland	-.469	-.006	-.14	-.293	-.215
Tanzania	-.242	-.057	-.108	-.152	-.149
Togo	-.327	-.042	-.093	-.109	-.132
Uganda	-.168	-.057	-.094	-.131	-.118
Zambia	-.396	0	-.175	-.328	-.314
Zimbabwe	-.379	-.099	-.202	-.328	-.312

Table A-32: Counterfactual GDP Losses (Share of GDP) - Middle East and North Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Algeria	-.36	-.019	-.031	-.037	-.033
Bahrain	-.219	0	-.007	-.01	-.01
Egypt	.113	0	.008	.01	.011
Iran	-.289	.002	-.017	-.027	-.026
Iraq	-.411	0	-.035	-.058	-.042
Jordan	-.27	-.019	-.028	-.029	-.027
Kuwait	-.219	0	-.007	-.01	-.012
Lebanon	-.27	-.012	-.015	-.014	-.016
Libya	-.124	0	-.008	-.011	-.008
Morocco	-.39	-.038	-.076	-.11	-.099
Oman	-.219	0	-.007	-.009	-.009
Qatar	-.219	0	-.003	-.003	-.003
Saudi Arabia	-.219	0	-.006	-.006	-.005
Syria	-.27	-.049	-.066	-.082	-.077
Tunisia	-.36	-.019	-.039	-.054	-.045
United Arab Emirates	-.219	0	-.003	-.002	-.003
Yemen	-.282	-.031	-.062	-.072	-.064

Table A-33: Counterfactual GDP Losses (Share of GDP) - Asia

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Afghanistan	-.247	-.086	-.131	-.167	-.169
Azerbaijan	-.226	-.044	-.058	-.073	-.066
Bangladesh	-.217	-.016	-.059	-.09	-.086
Bhutan	-.381	-.034	-.181	-.277	-.233
Brunei	-.179	0	-.004	-.003	0
Cambodia	-.271	0	-.065	-.085	-.068
China	-.072	-.036	-.043	-.045	-.045
Hong Kong	-.072	0	-.001	-.002	-.002
India	-.381	0	-.074	-.131	-.127
Japan	-.057	-.01	-.011	-.012	-.009
Kazakhstan	.114	-.031	-.036	-.03	-.031
Kyrgyzstan	-.059	-.039	-.061	-.063	-.049
Maldives	-.201	0	-.012	-.016	-.037
Myanmar	-.393	0	-.094	-.144	-.14
Nepal	-.173	-.07	-.093	-.12	-.114
Pakistan	-.304	.001	-.041	-.062	-.061
Philippines	-.234	0	-.036	-.053	-.051
South Korea	-.093	-.015	-.023	-.024	-.028
Sri Lanka	-.201	0	-.026	-.044	-.048
Tajikistan	-.059	-.097	-.081	-.085	-.08
Thailand	-.262	0	-.034	-.055	-.041
Uzbekistan	-.121	-.065	-.064	-.066	-.063
Vietnam	-.151	0	-.028	-.04	-.042

Table A-34: Counterfactual GDP Losses (Share of GDP) - South America

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Argentina	-.111	0	-.002	0	.001
Barbados	-.237	0	-.006	-.007	-.032
Bolivia	-.43	-.042	-.098	-.135	-.116
Brazil	-.169	0	-.01	-.015	-.013
Chile	-.244	-.009	-.02	-.026	-.024
Colombia	-.232	0	-.015	-.022	-.02
Ecuador	-.288	0	-.027	-.04	-.043
Honduras	-.237	-.006	-.039	-.058	-.039
Paraguay	-.43	0	-.049	-.058	-.036
Peru	-.306	-.005	-.037	-.06	-.058
Suriname	-.43	0	-.021	-.014	-.012
Trinidad and Tobago	-.237	0	-.012	-.016	-.016
Uruguay	-.43	-.008	-.031	-.039	-.031
Venezuela	-.319	0	-.012	-.014	-.014

Table A-35: Counterfactual GDP Losses (Share of GDP) - North and Central America

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Bahamas	-.237	0	-.007	-.008	-.002
Belize	-.237	0	-.021	-.021	-.026
Canada	-.022	-.007	-.018	-.018	-.016
Costa Rica	-.237	0	-.011	-.011	-.004
Dominican Republic	-.237	0	-.017	-.023	-.026
El Salvador	-.237	0	-.022	-.028	-.018
Guatemala	-.237	-.017	-.039	-.056	-.05
Haiti	-.237	-.045	-.09	-.123	-.121
Jamaica	-.237	0	-.023	-.035	-.033
Mexico	-.354	0	-.026	-.043	-.022
Nicaragua	-.237	0	-.038	-.047	-.036
Panama	-.237	0	-.017	-.029	-.027
United States	-.059	.003	0	0	.001

Table A-36: Counterfactual GDP Losses (Share of GDP) - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Albania	-.086	-.053	-.05	-.052	-.046
Armenia	-.226	-.089	-.099	-.106	-.103
Austria	-.05	-.029	-.032	-.032	-.029
Belarus	.031	.012	-.011	-.012	-.012
Belgium	-.067	-.015	-.018	-.018	-.017
Bosnia and Herzegovina	-.086	-.052	-.052	-.054	-.054
Bulgaria	-.086	-.054	-.051	-.051	-.049
Croatia	-.05	-.044	-.041	-.042	-.046
Cyprus	-.078	0	-.001	-.001	.002
Czech Republic	-.05	-.021	-.031	-.032	-.026
Denmark	.109	.006	0	0	.005
Estonia	.031	.033	.009	.008	.002
Finland	.109	.02	.003	.003	-.001
France	-.067	-.027	-.027	-.028	-.027
Georgia	-.226	-.091	-.1	-.127	-.107
Germany	-.029	-.021	-.025	-.025	-.025
Greece	-.078	-.012	-.012	-.013	-.017
Hungary	-.05	-.05	-.048	-.048	-.049
Iceland	.109	.009	.005	.005	.014
Ireland	-.039	0	-.001	-.001	-.001
Israel	-.27	0	-.004	-.005	-.009
Italy	-.074	-.018	-.017	-.017	-.018

Table A-37: Counterfactual GDP Losses (Share of GDP) - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Latvia	.031	.032	.006	.006	.009
Lithuania	.031	.018	-.005	-.005	-.004
Luxembourg	-.05	-.018	-.016	-.016	-.018
Macedonia	-.086	-.061	-.059	-.059	-.054
Malta	-.074	0	-.001	-.001	-.004
Moldova	-.086	-.07	-.071	-.073	-.051
Montenegro	-.086	-.03	-.032	-.031	-.035
Netherlands	-.07	-.007	-.01	-.01	-.014
Norway	.109	-.006	-.004	-.004	-.002
Poland	-.047	-.01	-.024	-.025	-.023
Portugal	-.096	-.009	-.011	-.013	-.013
Romania	-.066	-.056	-.054	-.057	-.061
Russia	-.077	-.006	-.026	-.027	-.026
Serbia	-.086	-.075	-.069	-.07	-.063
Slovakia	-.05	-.032	-.039	-.039	-.038
Slovenia	-.05	-.039	-.039	-.04	-.036
Spain	-.089	-.012	-.011	-.012	-.009
Sweden	.109	.011	-.002	-.002	-.005
Switzerland	-.05	-.031	-.031	-.031	-.035
Turkey	-.162	-.038	-.039	-.042	-.041
Ukraine	-.052	-.038	-.045	-.046	-.042
United Kingdom	-.039	-.002	-.004	-.004	-.003

Table A-38: Counterfactual GDP Losses (Share of GDP) - Western Pacific and Oceania

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Australia	-.266	0	-.004	-.005	-.006
Fiji	.022	-.004	.001	.003	-.013
Indonesia	-.179	0	-.023	-.034	-.027
Malaysia	-.225	0	-.012	-.013	-.012
New Zealand	.022	0	0	0	.009
Singapore	-.225	0	-.005	-.006	-.01

Table A-39: Equivalent Variation Willingness-to-Pay (Share of GDP) - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Angola	-.258	0	-.083	-.019	-.018
Benin	-.327	0	-.276	-.078	-.069
Botswana	-.469	0	-.423	-.116	-.087
Burkina Faso	-.243	0	-.226	-.07	-.063
Cameroon	-.2	-.005	-.18	-.055	-.052
Cape Verde	-.327	-.012	-.344	-.12	-.046
Central African Republic	-.601	-.076	-.723	-.428	-.356
Chad	-.601	0	-.67	-.25	-.226
Comoros	-.217	-.075	-.222	-.102	-.065
Congo	-.601	0	-.66	-.225	-.079
Cote d'Ivoire	-.143	0	-.093	-.025	-.025
Democratic Republic of Congo	-.147	-.142	-.209	-.131	-.129
Ethiopia	-.313	-.102	-.364	-.171	-.169
Gabon	-.601	0	-.572	-.15	-.069
Gambia	-.327	0	-.261	-.072	-.133
Ghana	-.14	0	-.07	-.018	-.014
Kenya	-.054	-.044	-.052	-.035	-.031
Lesotho	-.469	-.055	-.432	-.147	-.072
Madagascar	-.262	-.067	-.324	-.153	-.146

Table A-40: Equivalent Variation Willingness-to-Pay (Share of GDP) - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Malawi	-.313	-.111	-.4	-.225	-.225
Mali	-.356	0	-.359	-.115	-.106
Mauritania	-.327	0	-.36	-.126	-.101
Mauritius	-.262	0	-.057	-.013	-.007
Mozambique	-.217	-.104	-.279	-.143	-.147
Namibia	-.469	0	-.328	-.076	-.044
Niger	-.341	0	-.402	-.163	-.121
Nigeria	-.185	0	-.054	-.013	-.012
Rwanda	-.601	-.058	-.725	-.434	-.387
Senegal	-.519	0	-.513	-.155	-.08
Seychelles	-.262	0	-.064	-.014	-.023
Sierra Leone	-.327	-.071	-.33	-.13	-.164
Somalia	-.166	-.125	-.22	-.126	-.123
South Africa	-.334	0	-.103	-.022	-.019
Sudan	-.561	0	-.436	-.101	-.087
Swaziland	-.469	-.006	-.504	-.172	-.121
Tanzania	-.242	-.057	-.268	-.112	-.109
Togo	-.327	-.042	-.289	-.099	-.125
Uganda	-.168	-.057	-.205	-.096	-.085
Zambia	-.396	0	-.481	-.208	-.199
Zimbabwe	-.379	-.099	-.464	-.223	-.212

Table A-41: Equivalent Variation Willingness-to-Pay (Share of GDP) - Middle East and North Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Algeria	-.36	-.019	-.104	-.031	-.028
Bahrain	-.219	0	-.034	-.007	-.008
Egypt	.113	0	.028	.008	.009
Iran	-.289	.002	-.085	-.018	-.016
Iraq	-.411	0	-.192	-.04	-.031
Jordan	-.27	-.019	-.082	-.028	-.026
Kuwait	-.219	0	-.032	-.007	-.01
Lebanon	-.27	-.012	-.037	-.014	-.015
Libya	-.124	0	-.033	-.008	-.005
Morocco	-.39	-.038	-.252	-.08	-.076
Oman	-.219	0	-.033	-.007	-.007
Qatar	-.219	0	-.013	-.003	-.003
Saudi Arabia	-.219	0	-.029	-.006	-.005
Syria	-.27	-.049	-.164	-.065	-.063
Tunisia	-.36	-.019	-.141	-.041	-.035
United Arab Emirates	-.219	0	-.014	-.003	-.002
Yemen	-.282	-.031	-.191	-.063	-.056

Table A-42: Equivalent Variation Willingness-to-Pay (Share of GDP) - Asia

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Afghanistan	-.247	-.086	-.28	-.133	-.134
Azerbaijan	-.226	-.044	-.139	-.057	-.053
Bangladesh	-.217	-.016	-.189	-.062	-.058
Bhutan	-.381	-.034	-.466	-.208	-.173
Brunei	-.179	0	-.019	-.004	-.004
Cambodia	-.271	0	-.237	-.07	-.057
China	-.072	-.036	-.057	-.04	-.04
Hong Kong	-.072	0	-.006	-.001	-.001
India	-.381	0	-.311	-.085	-.082
Japan	-.057	-.01	-.015	-.011	-.008
Kazakhstan	.114	-.031	-.01	-.034	-.035
Kyrgyzstan	-.059	-.039	-.078	-.058	-.047
Maldives	-.201	0	-.052	-.012	-.017
Myanmar	-.393	0	-.367	-.109	-.105
Nepal	-.173	-.07	-.192	-.092	-.084
Pakistan	-.304	.001	-.179	-.045	-.044
Philippines	-.234	0	-.145	-.038	-.038
South Korea	-.093	-.015	-.032	-.021	-.024
Sri Lanka	-.201	0	-.105	-.027	-.03
Tajikistan	-.059	-.097	-.1	-.078	-.074
Thailand	-.262	0	-.144	-.036	-.028
Uzbekistan	-.121	-.065	-.088	-.061	-.057
Vietnam	-.151	0	-.101	-.028	-.029

Table A-43: Equivalent Variation Willingness-to-Pay (Share of GDP) - South America

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Argentina	-.111	0	-.008	-.002	0
Barbados	-.237	0	-.029	-.006	-.029
Bolivia	-.43	-.042	-.343	-.108	-.095
Brazil	-.169	0	-.041	-.01	-.008
Chile	-.244	-.009	-.068	-.02	-.019
Colombia	-.232	0	-.067	-.015	-.013
Ecuador	-.288	0	-.123	-.028	-.031
Honduras	-.237	-.006	-.153	-.041	-.032
Paraguay	-.43	0	-.255	-.057	-.037
Peru	-.306	-.005	-.162	-.04	-.04
Suriname	-.43	0	-.125	-.024	-.008
Trinidad and Tobago	-.237	0	-.057	-.013	-.012
Uruguay	-.43	-.008	-.151	-.034	-.028
Venezuela	-.319	0	-.064	-.013	-.012

Table A-44: Equivalent Variation Willingness-to-Pay (Share of GDP) - North and Central America

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Bahamas	-.237	0	-.035	-.008	-.002
Belize	-.237	0	-.091	-.021	-.024
Canada	-.022	-.007	-.018	-.016	-.014
Costa Rica	-.237	0	-.052	-.011	-.004
Dominican Republic	-.237	0	-.075	-.017	-.022
El Salvador	-.237	0	-.095	-.023	-.015
Guatemala	-.237	-.017	-.128	-.04	-.036
Haiti	-.237	-.045	-.237	-.093	-.091
Jamaica	-.237	0	-.099	-.024	-.024
Mexico	-.354	0	-.132	-.028	-.015
Nicaragua	-.237	0	-.151	-.039	-.031
Panama	-.237	0	-.076	-.017	-.018
United States	-.059	.003	-.002	0	.001

Table A-45: Equivalent Variation Willingness-to-Pay (Share of GDP) - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Albania	-.086	-.053	-.067	-.047	-.04
Armenia	-.226	-.089	-.176	-.095	-.087
Austria	-.05	-.029	-.033	-.029	-.026
Belarus	.031	.012	-.006	-.011	-.011
Belgium	-.067	-.015	-.02	-.017	-.016
Bosnia and Herzegovina	-.086	-.052	-.065	-.049	-.049
Bulgaria	-.086	-.054	-.058	-.047	-.045
Croatia	-.05	-.044	-.045	-.038	-.041
Cyprus	-.078	0	-.005	-.001	.002
Czech Republic	-.05	-.021	-.034	-.029	-.024
Denmark	.109	.006	.003	0	.005
Estonia	.031	.033	.011	.008	.002
Finland	.109	.02	.008	.003	-.001
France	-.067	-.027	-.029	-.025	-.024
Georgia	-.226	-.091	-.193	-.098	-.084
Germany	-.029	-.021	-.025	-.023	-.023
Greece	-.078	-.012	-.018	-.011	-.015
Hungary	-.05	-.05	-.05	-.045	-.045
Iceland	.109	.009	.009	.005	.014
Ireland	-.039	0	-.003	-.001	-.002
Israel	-.27	0	-.022	-.005	-.009
Italy	-.074	-.018	-.02	-.016	-.016

Table A-46: Equivalent Variation Willingness-to-Pay (Share of GDP) - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Latvia	.031	.032	.009	.006	.008
Lithuania	.031	.018	-.001	-.004	-.003
Luxembourg	-.05	-.018	-.017	-.015	-.017
Macedonia	-.086	-.061	-.07	-.055	-.049
Malta	-.074	0	-.006	-.001	-.005
Moldova	-.086	-.07	-.09	-.067	-.048
Montenegro	-.086	-.03	-.04	-.03	-.032
Netherlands	-.07	-.007	-.012	-.009	-.012
Norway	.109	-.006	-.001	-.003	-.002
Poland	-.047	-.01	-.029	-.022	-.02
Portugal	-.096	-.009	-.02	-.01	-.011
Romania	-.066	-.056	-.065	-.051	-.053
Russia	-.077	-.006	-.031	-.024	-.023
Serbia	-.086	-.075	-.08	-.064	-.057
Slovakia	-.05	-.032	-.041	-.036	-.035
Slovenia	-.05	-.039	-.043	-.036	-.033
Spain	-.089	-.012	-.016	-.011	-.008
Sweden	.109	.011	.002	-.002	-.005
Switzerland	-.05	-.031	-.032	-.028	-.032
Turkey	-.162	-.038	-.06	-.036	-.036
Ukraine	-.052	-.038	-.054	-.042	-.037
United Kingdom	-.039	-.002	-.005	-.004	-.003

Table A-47: Equivalent Variation Willingness-to-Pay (Share of GDP) - Western Pacific and Oceania

Country	Ag Productivity Change	Manufacturing Productivity Change	No Reallocation	Autarky	With Trade
Australia	-.266	0	-.019	-.004	-.005
Fiji	.022	-.004	.008	.001	-.007
Indonesia	-.179	0	-.092	-.023	-.018
Malaysia	-.225	0	-.054	-.012	-.012
New Zealand	.022	0	.001	0	.009
Singapore	-.225	0	-.025	-.005	-.009

Table A-48: Counterfactual Change in Food Prices - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Angola	-.258	0	34.771	25.884
Benin	-.327	0	48.593	28.345
Botswana	-.469	0	88.326	46.253
Burkina Faso	-.243	0	32.099	27.752
Cameroon	-.2	-.005	25	23.809
Cape Verde	-.327	-.012	48.589	30.641
Central African Republic	-.601	-.076	150.624	36.303
Chad	-.601	0	150.634	117.717
Comoros	-.217	-.075	27.717	22.011
Congo	-.601	0	150.629	32.426
Cote d'Ivoire	-.143	0	16.691	18.443
Democratic Republic of Congo	-.147	-.142	17.231	10.576
Ethiopia	-.313	-.102	45.554	30.082
Gabon	-.601	0	150.632	34.985
Gambia	-.327	0	48.586	16.877
Ghana	-.14	0	16.282	20.566
Kenya	-.054	-.044	5.708	9.776
Lesotho	-.469	-.055	88.331	48.302
Madagascar	-.262	-.067	35.499	21.645

Table A-49: Counterfactual Change in Food Prices - Sub-Saharan Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Malawi	-.313	-.111	45.559	21.76
Mali	-.356	0	55.278	34.724
Mauritania	-.327	0	48.587	23.488
Mauritius	-.262	0	35.502	18.92
Mozambique	-.217	-.104	27.716	21.893
Namibia	-.469	0	88.323	38.591
Niger	-.341	0	51.744	50.943
Nigeria	-.185	0	22.699	22.24
Rwanda	-.601	-.058	150.628	51.389
Senegal	-.519	0	107.898	37.364
Seychelles	-.262	0	35.505	13.96
Sierra Leone	-.327	-.071	48.58	8.697
Somalia	-.166	-.125	19.904	17.825
South Africa	-.334	0	50.144	28.951
Sudan	-.561	0	127.79	69.284
Swaziland	-.469	-.006	88.323	46.552
Tanzania	-.242	-.057	31.926	23.751
Togo	-.327	-.042	48.589	15.661
Uganda	-.168	-.057	20.191	21.826
Zambia	-.396	0	65.563	45.63
Zimbabwe	-.379	-.099	61.035	35.921

Table A-50: Counterfactual Change in Food Prices - Middle East and North Africa

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Algeria	-.36	-.019	56.251	32.033
Bahrain	-.219	0	28.033	19.754
Egypt	.113	0	-10.152	2.943
Iran	-.289	.002	40.648	33.444
Iraq	-.411	0	69.775	32.181
Jordan	-.27	-.019	36.986	18.564
Kuwait	-.219	0	28.04	19.881
Lebanon	-.27	-.012	36.987	28.029
Libya	-.124	0	14.156	11.629
Morocco	-.39	-.038	63.943	27.302
Oman	-.219	0	28.039	17.587
Qatar	-.219	0	28.04	25.392
Saudi Arabia	-.219	0	28.041	20.696
Syria	-.27	-.049	36.986	23.632
Tunisia	-.36	-.019	56.25	28.447
United Arab Emirates	-.219	0	28.041	17.641
Yemen	-.282	-.031	39.278	25.125

Table A-51: Counterfactual Change in Food Prices - Asia

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Afghanistan	-.247	-.086	32.806	21.242
Azerbaijan	-.226	-.044	29.197	16.818
Bangladesh	-.217	-.016	27.714	25.683
Bhutan	-.381	-.034	61.553	40.819
Brunei	-.179	0	21.806	21.636
Cambodia	-.271	0	37.173	35.462
China	-.072	-.036	7.765	7.913
Hong Kong	-.072	0	7.758	10.497
India	-.381	0	61.556	47.244
Japan	-.057	-.01	6.041	9.157
Kazakhstan	.114	-.031	-10.235	-5.317
Kyrgyzstan	-.059	-.039	6.268	10.307
Maldives	-.201	0	25.163	20.722
Myanmar	-.393	0	64.742	41.112
Nepal	-.173	-.07	20.924	19.834
Pakistan	-.304	.001	43.678	40.005
Philippines	-.234	0	30.548	19.969
South Korea	-.093	-.015	10.254	12.046
Sri Lanka	-.201	0	25.158	17.877
Tajikistan	-.059	-.097	6.269	6.705
Thailand	-.262	0	35.503	17.386
Uzbekistan	-.121	-.065	13.766	12.432
Vietnam	-.151	0	17.786	17.872

Table A-52: Counterfactual Change in Food Prices - South America

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Argentina	-.111	0	12.486	14.87
Barbados	-.237	0	31.062	17.803
Bolivia	-.43	-.042	75.439	38.358
Brazil	-.169	0	20.34	18.347
Chile	-.244	-.009	32.277	22.685
Colombia	-.232	0	30.204	22.204
Ecuador	-.288	0	40.448	19.993
Honduras	-.237	-.006	31.063	16.769
Paraguay	-.43	0	75.435	27.023
Peru	-.306	-.005	44.091	23.927
Suriname	-.43	0	75.436	24.519
Trinidad and Tobago	-.237	0	31.057	12.666
Uruguay	-.43	-.008	75.436	31.877
Venezuela	-.319	0	46.837	34.644

Table A-53: Counterfactual Change in Food Prices - North and Central America

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Bahamas	-.237	0	31.065	13.332
Belize	-.237	0	31.065	16.946
Canada	-.022	-.007	2.25	9.276
Costa Rica	-.237	0	31.057	14.191
Dominican Republic	-.237	0	31.058	16.654
El Salvador	-.237	0	31.067	23.574
Guatemala	-.237	-.017	31.069	19.503
Haiti	-.237	-.045	31.062	17.404
Jamaica	-.237	0	31.056	13.549
Mexico	-.354	0	54.8	20.538
Nicaragua	-.237	0	31.06	16.92
Panama	-.237	0	31.06	18.066
United States	-.059	.003	6.27	9.093

Table A-54: Counterfactual Change in Food Prices - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Albania	-.086	-.053	9.409	13.132
Armenia	-.226	-.089	29.201	23.965
Austria	-.05	-.029	5.271	6.526
Belarus	.031	.012	-3.007	4.566
Belgium	-.067	-.015	7.18	9.457
Bosnia and Herzegovina	-.086	-.052	9.409	7.077
Bulgaria	-.086	-.054	9.408	9.092
Croatia	-.05	-.044	5.262	4.027
Cyprus	-.078	0	8.46	11.172
Czech Republic	-.05	-.021	5.263	7.433
Denmark	.109	.006	-9.829	4.623
Estonia	.031	.033	-3.007	4.376
Finland	.109	.02	-9.828	-2.956
France	-.067	-.027	7.181	8.486
Georgia	-.226	-.091	29.198	14.232
Germany	-.029	-.021	2.986	9.173
Greece	-.078	-.012	8.461	8.65
Hungary	-.05	-.05	5.263	6.162
Iceland	.109	.009	-9.829	5.09
Ireland	-.039	0	4.056	6.307
Israel	-.27	0	36.987	23.532
Italy	-.074	-.018	7.99	8.789

Table A-55: Counterfactual Change in Food Prices - Europe

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Latvia	.031	.032	-3.007	6.174
Lithuania	.031	.018	-3.002	5.743
Luxembourg	-.05	-.018	5.263	7.257
Macedonia	-.086	-.061	9.405	7.019
Malta	-.074	0	7.991	7.718
Moldova	-.086	-.07	9.416	11.68
Montenegro	-.086	-.03	9.41	7.236
Netherlands	-.07	-.007	7.527	10.548
Norway	.109	-.006	-9.83	3.725
Poland	-.047	-.01	4.931	7.639
Portugal	-.096	-.009	10.619	10.082
Romania	-.066	-.056	7.067	6.077
Russia	-.077	-.006	8.343	10.246
Serbia	-.086	-.075	9.41	6.876
Slovakia	-.05	-.032	5.263	6.094
Slovenia	-.05	-.039	5.268	7.708
Spain	-.089	-.012	9.768	10.424
Sweden	.109	.011	-9.828	.349
Switzerland	-.05	-.031	5.259	8.984
Turkey	-.162	-.038	19.33	14.43
Ukraine	-.052	-.038	5.492	9.617
United Kingdom	-.039	-.002	4.057	7.879

Table A-56: Counterfactual Change in Food Prices - Western Pacific and Oceania

Country	Ag Productivity Change	Manufacturing Productivity Change	Autarky	With Trade
Australia	-.266	0	36.24	24.799
Fiji	.022	-.004	-2.152	12.003
Indonesia	-.179	0	21.805	20.004
Malaysia	-.225	0	29.027	18.33
New Zealand	.022	0	-2.152	11.207
Singapore	-.225	0	29.03	15.615

Table A-57: Equivalent Variation Willingness-to-Pay (Share of GDP) Alternative Trade Cost Cases - Sub-Saharan Africa

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Angola	-.019	-.018	.003
Benin	-.078	-.069	.009
Botswana	-.116	-.087	.003
Burkina Faso	-.07	-.063	-.038
Cameroon	-.055	-.052	.011
Cape Verde	-.12	-.046	-.023
Central African Republic	-.428	-.356	-.037
Chad	-.25	-.226	-.032
Comoros	-.102	-.065	-.03
Congo	-.225	-.079	.009
Cote d'Ivoire	-.025	-.025	-.016
Democratic Republic of Congo	-.131	-.129	-.12
Ethiopia	-.171	-.169	-.091
Gabon	-.15	-.069	.001
Gambia	-.072	-.133	-.091
Ghana	-.018	-.014	-.017
Kenya	-.035	-.031	-.045
Lesotho	-.147	-.072	-.085
Madagascar	-.153	-.146	-.073

Table A-58: Equivalent Variation Willingness-to-Pay (Share of GDP) Alternative Trade Cost Cases - Sub-Saharan Africa

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Malawi	-.225	-.225	-.119
Mali	-.115	-.106	-.005
Mauritania	-.126	-.101	.003
Mauritius	-.013	-.007	-.01
Mozambique	-.143	-.147	-.074
Namibia	-.076	-.044	-.003
Niger	-.163	-.121	-.056
Nigeria	-.013	-.012	-.006
Rwanda	-.434	-.387	-.086
Senegal	-.155	-.08	-.046
Seychelles	-.014	-.023	.038
Sierra Leone	-.13	-.164	-.105
Somalia	-.126	-.123	-.103
South Africa	-.022	-.019	-.008
Sudan	-.101	-.087	-.024
Swaziland	-.172	-.121	-.013
Tanzania	-.112	-.109	-.061
Togo	-.099	-.125	-.066
Uganda	-.096	-.085	-.049
Zambia	-.208	-.199	-.001
Zimbabwe	-.223	-.212	-.074

Table A-59: Equivalent Variation Willingness-to-Pay (Share of GDP) Alternative Trade Cost Cases - Middle East and North Africa

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Algeria	-.031	-.028	-.019
Bahrain	-.007	-.008	-.001
Egypt	.008	.009	0
Iran	-.018	-.016	-.004
Iraq	-.04	-.031	-.004
Jordan	-.028	-.026	-.026
Kuwait	-.007	-.01	0
Lebanon	-.014	-.015	-.022
Libya	-.008	-.005	-.009
Morocco	-.08	-.076	-.029
Oman	-.007	-.007	-.009
Qatar	-.003	-.003	-.002
Saudi Arabia	-.006	-.005	-.001
Syria	-.065	-.063	-.047
Tunisia	-.041	-.035	-.048
United Arab Emirates	-.003	-.002	-.002
Yemen	-.063	-.056	-.028

Table A-60: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases - Asia

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Afghanistan	-.133	-.134	-.075
Azerbaijan	-.057	-.053	-.035
Bangladesh	-.062	-.058	-.022
Bhutan	-.208	-.173	.013
Brunei	-.004	-.004	.005
Cambodia	-.07	-.057	.002
China	-.04	-.04	-.04
Hong Kong	-.001	-.001	-.004
India	-.085	-.082	-.013
Japan	-.011	-.008	-.01
Kazakhstan	-.034	-.035	-.038
Kyrgyzstan	-.058	-.047	-.052
Maldives	-.012	-.017	-.035
Myanmar	-.109	-.105	.002
Nepal	-.092	-.084	-.064
Pakistan	-.045	-.044	-.034
Philippines	-.038	-.038	-.006
South Korea	-.021	-.024	-.017
Sri Lanka	-.027	-.03	0
Tajikistan	-.078	-.074	-.119
Thailand	-.036	-.028	-.002
Uzbekistan	-.061	-.057	-.049
Vietnam	-.028	-.029	-.01

Table A-61: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases - South America

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Argentina	-.002	0	-.006
Barbados	-.006	-.029	-.01
Bolivia	-.108	-.095	-.036
Brazil	-.01	-.008	-.006
Chile	-.02	-.019	-.01
Colombia	-.015	-.013	-.006
Ecuador	-.028	-.031	-.003
Honduras	-.041	-.032	-.011
Paraguay	-.057	-.037	-.03
Peru	-.04	-.04	-.008
Suriname	-.024	-.008	-.015
Trinidad and Tobago	-.013	-.012	.004
Uruguay	-.034	-.028	-.014
Venezuela	-.013	-.012	-.001

Table A-62: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases - North and Central America

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Bahamas	-.008	-.002	-.029
Belize	-.021	-.024	-.001
Canada	-.016	-.014	-.016
Costa Rica	-.011	-.004	-.021
Dominican Republic	-.017	-.022	.004
El Salvador	-.023	-.015	-.021
Guatemala	-.04	-.036	-.019
Haiti	-.093	-.091	-.048
Jamaica	-.024	-.024	.02
Mexico	-.028	-.015	-.003
Nicaragua	-.039	-.031	-.021
Panama	-.017	-.018	-.002
United States	0	.001	0

Table A-63: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases - Europe

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Albania	-.047	-.04	-.047
Armenia	-.095	-.087	-.077
Austria	-.029	-.026	-.031
Belarus	-.011	-.011	-.007
Belgium	-.017	-.016	-.015
Bosnia and Herzegovina	-.049	-.049	-.065
Bulgaria	-.047	-.045	-.033
Croatia	-.038	-.041	-.03
Cyprus	-.001	.002	.003
Czech Republic	-.029	-.024	-.027
Denmark	0	.005	.005
Estonia	.008	.002	.02
Finland	.003	-.001	.006
France	-.025	-.024	-.021
Georgia	-.098	-.084	-.075
Germany	-.023	-.023	-.021
Greece	-.011	-.015	-.007
Hungary	-.045	-.045	-.035
Iceland	.005	.014	.009
Ireland	-.001	-.002	-.003
Israel	-.005	-.009	-.012
Italy	-.016	-.016	-.015

Table A-64: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases - Europe

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Latvia	.006	.008	.005
Lithuania	-.004	-.003	-.015
Luxembourg	-.015	-.017	-.008
Macedonia	-.055	-.049	-.053
Malta	-.001	-.005	.006
Moldova	-.067	-.048	-.05
Montenegro	-.03	-.032	-.016
Netherlands	-.009	-.012	-.006
Norway	-.003	-.002	-.004
Poland	-.022	-.02	-.025
Portugal	-.01	-.011	-.007
Romania	-.051	-.053	-.042
Russia	-.024	-.023	-.025
Serbia	-.064	-.057	-.071
Slovakia	-.036	-.035	-.031
Slovenia	-.036	-.033	-.044
Spain	-.011	-.008	-.007
Sweden	-.002	-.005	.004
Switzerland	-.028	-.032	-.022
Turkey	-.036	-.036	-.03
Ukraine	-.042	-.037	-.046
United Kingdom	-.004	-.003	0

Table A-65: Equivalent Variation Willingness-to-Pay (Share of GDP)
Alternative Trade Cost Cases - Western Pacific and Oceania

Country	Autarky	Estimated Trade Cost Case	Low Trade Cost Case
Australia	-.004	-.005	-.003
Fiji	.001	-.007	.008
Indonesia	-.023	-.018	-.006
Malaysia	-.012	-.012	-.001
New Zealand	0	.009	.002
Singapore	-.005	-.009	0

Table A-66: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - Sub-Saharan Africa

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counter-factual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Angola	2.09	.05	.034	.033	-.029	-.008
Benin	1.63	.156	.121	.074	-.131	-.033
Botswana	3.28	.062	.034	.019	-.087	-.035
Burkina Faso	1.2	.24	.187	.23	-.09	-.075
Cameroon	1.68	.216	.145	.166	-.106	-.051
Cape Verde	1.43	.163	.083	.06	-.05	-.084
Central African Republic	1.47	.299	.287	.094	-.436	-.316
Chad	1.13	.257	.213	.243	-.226	-.221
Comoros	1.34	.083	.053	.006	-.081	.088
Congo	2.73	.092	.046	.005	-.093	-.046
Cote d'Ivoire	1.39	.17	.132	.14	-.064	-.033
Democratic Republic of Congo	10.19	.421	.151	.169	-.159	-.027
Ethiopia	1.23	.359	.333	.376	-.19	-.182
Gabon	1.23	.073	.065	.006	-.069	-.04
Gambia	1.24	.008	.074	.027	-.206	-.133
Ghana	1.65	.181	.143	.164	-.024	-.011
Kenya	2.59	.156	.102	.109	-.049	-.017
Lesotho	1.56	.107	.045	.03	-.081	-.121
Madagascar	1.8	.404	.299	.275	-.154	-.127

Table A-67: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - Sub-Saharan Africa

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counter-factual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Malawi	2.84	.436	.309	.357	-.244	-.167
Mali	1.81	.197	.147	.146	-.126	-.067
Mauritania	1.98	.249	.157	.149	-.101	-.074
Mauritius	1.69	.038	.017	.028	-.009	-.008
Mozambique	1.92	.367	.267	.305	-.169	-.13
Namibia	2.29	.099	.06	.027	-.044	-.035
Niger	1.97	.325	.196	.248	-.193	-.125
Nigeria	2.16	.068	.045	.049	-.012	-.008
Rwanda	1.14	.409	.39	.322	-.394	-.366
Senegal	1.24	.153	.1	.047	-.105	-.101
Seychelles	2.03	.016	.031	.004	-.023	.038
Sierra Leone	1.49	.139	.177	.173	-.204	-.146
Somalia	2.27	.334	.201	.219	-.176	-.152
South Africa	2.7	.056	.036	.03	-.033	-.012
Sudan	1.67	.12	.092	.068	-.087	-.065
Swaziland	1.92	.102	.058	.034	-.135	-.091
Tanzania	1.19	.298	.239	.318	-.131	-.123
Togo	1.26	.316	.277	.302	-.183	-.149
Uganda	1.25	.416	.338	.404	-.109	-.115
Zambia	1.52	.36	.28	.318	-.233	-.181
Zimbabwe	4.17	.302	.122	.14	-.248	-.111

Table A-68: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - Middle East and North Africa

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counterfactual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Algeria	1.96	.034	.022	.015	-.068	-.029
Bahrain	2	.015	.013	.006	-.008	-.008
Egypt	2.08	.077	.049	.07	.009	.006
Iran	1.62	.051	.038	.042	-.067	-.019
Iraq	2.9	.05	.023	.019	-.031	-.018
Jordan	2.53	.038	.032	.025	-.055	-.007
Kuwait	1.19	.005	.003	.004	-.01	-.005
Lebanon	1.91	.079	.058	.056	-.034	-.007
Libya	2.07	.067	.043	.048	-.026	-.01
Morocco	1.44	.1	.086	.048	-.093	-.071
Oman	1.14	.023	.018	.015	-.007	-.01
Qatar	1.92	.008	.007	.005	-.003	0
Saudi Arabia	1.43	.016	.011	.011	-.005	-.004
Syria	1.54	.09	.058	.058	-.106	-.094
Tunisia	2.77	.055	.037	.021	-.068	-.016
United Arab Emirates	1.97	.016	.011	.013	-.002	-.001
Yemen	7.17	.11	.04	.04	-.086	-.018

Table A-69: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - Asia

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counter-factual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Afghanistan	2.19	.278	.186	.218	-.158	-.134
Azerbaijan	2.23	.088	.055	.054	-.075	-.054
Bangladesh	1.52	.189	.144	.165	-.093	-.058
Bhutan	3.4	.267	.134	.075	-.179	-.076
Brunei	.71	.027	.006	.023	-.004	-.007
Cambodia	4.62	.19	.092	.085	-.064	-.019
China	3.48	.064	.034	.038	-.065	-.03
Hong Kong	1.92	.018	.012	.013	-.001	-.002
India	3.24	.161	.087	.106	-.082	-.045
Japan	1.72	.012	.008	.009	-.017	-.007
Kazakhstan	2.23	.088	.056	.06	-.05	-.044
Kyrgyzstan	10.26	.156	.041	.062	-.062	-.069
Maldives	1.77	.021	.03	.073	-.023	-.04
Myanmar	2.13	.209	.144	.179	-.111	-.071
Nepal	1.52	.283	.223	.277	-.109	-.103
Pakistan	1.69	.133	.103	.111	-.06	-.031
Philippines	1.99	.105	.07	.064	-.038	-.022
South Korea	1.54	.012	.007	.009	-.035	-.022
Sri Lanka	1.28	.109	.105	.099	-.03	-.02
Tajikistan	10.58	.232	.075	.081	-.101	-.06
Thailand	2.61	.072	.045	.033	-.028	-.014
Uzbekistan	9.37	.108	.04	.044	-.092	-.005
Vietnam	4.55	.158	.078	.082	-.049	-.014

Table A-70: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - South America

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counterfactual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Argentina	2.1	.065	.051	.058	-.009	-.002
Barbados	1.19	.035	.055	.047	-.029	-.008
Bolivia	1.79	.125	.096	.071	-.132	-.105
Brazil	2.46	.063	.041	.043	-.008	-.009
Chile	1.89	.053	.035	.029	-.022	-.014
Colombia	1.92	.066	.047	.051	-.031	-.011
Ecuador	1.79	.098	.075	.067	-.043	-.021
Honduras	1.52	.082	.061	.045	-.072	-.04
Paraguay	2	.151	.079	.062	-.048	-.046
Peru	1.91	.104	.073	.063	-.064	-.029
Suriname	2.35	.028	.019	.006	-.008	-.019
Trinidad and Tobago	1.85	.004	.009	.002	-.012	-.004
Uruguay	2.25	.091	.062	.018	-.031	-.014
Venezuela	2.33	.027	.017	.016	-.012	-.005

Table A-71: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - North and Central America

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counterfactual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Bahamas	1.84	.02	.006	.011	-.002	-.024
Belize	1.8	.104	.083	.097	-.024	.009
Canada	1.63	.019	.014	.02	-.02	-.02
Costa Rica	1.38	.021	.015	.015	-.004	-.017
Dominican Republic	1.74	.046	.035	.027	-.022	-.008
El Salvador	1.92	.108	.059	.064	-.015	-.02
Guatemala	1.69	.151	.118	.116	-.057	-.035
Haiti	2.45	.161	.12	.134	-.123	-.067
Jamaica	3.38	.074	.041	.033	-.024	-.006
Mexico	2.62	.031	.019	.009	-.015	-.009
Nicaragua	1.9	.11	.061	.079	-.061	-.028
Panama	1.74	.06	.048	.035	-.018	-.009
United States	1.96	.023	.017	.022	-.011	0

Table A-72: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - Europe

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counterfactual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Albania	2.08	.129	.077	.058	-.056	-.049
Armenia	4.46	.104	.047	.05	-.106	-.074
Austria	1.6	.012	.008	.01	-.039	-.039
Belarus	2.2	.05	.033	.039	-.016	-.023
Belgium	1.69	.02	.012	.015	-.02	-.019
Bosnia and Herzegovina	3.79	.047	.025	.039	-.061	-.05
Bulgaria	1.86	.06	.041	.046	-.06	-.045
Croatia	2.16	.042	.029	.037	-.06	-.038
Cyprus	2.66	.06	.033	.046	.002	0
Czech Republic	1.61	.018	.011	.013	-.036	-.038
Denmark	1.76	.033	.025	.039	.005	.001
Estonia	1.95	.036	.036	.029	.001	.01
Finland	1.81	.013	.009	.014	-.002	-.002
France	1.81	.026	.019	.025	-.035	-.024
Georgia	4.68	.086	.032	.031	-.1	-.06
Germany	1.75	.011	.007	.01	-.032	-.026
Greece	1.89	.037	.028	.028	-.033	-.008
Hungary	2.4	.028	.02	.023	-.07	-.045
Iceland	2.2	.063	.059	.075	.015	.008
Ireland	1.7	.002	.003	.003	-.002	-.002
Israel	2.19	.016	.01	.006	-.009	.003
Italy	2.21	.019	.012	.014	-.035	-.014

Table A-73: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - Europe

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counterfactual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Latvia	2.37	.037	.034	.045	.006	-.008
Lithuania	2.04	.035	.029	.031	-.006	-.021
Luxembourg	2.18	.013	.01	.011	-.026	-.008
Macedonia	3.82	.104	.056	.064	-.064	-.046
Malta	2.56	.006	.009	.015	-.013	.003
Moldova	8.94	.169	.036	.062	-.06	-.052
Montenegro	2.06	.054	.041	.046	-.041	-.032
Netherlands	2.1	.027	.019	.022	-.014	-.005
Norway	1.71	.02	.012	.026	-.002	-.002
Poland	2.3	.031	.019	.024	-.028	-.029
Portugal	2.73	.026	.015	.018	-.014	.001
Romania	2.81	.06	.036	.041	-.072	-.045
Russia	2.16	.03	.02	.023	-.028	-.034
Serbia	3.55	.069	.037	.045	-.081	-.06
Slovakia	1.71	.022	.014	.015	-.05	-.047
Slovenia	1.5	.017	.01	.014	-.048	-.054
Spain	1.88	.023	.016	.018	-.023	-.003
Sweden	1.7	.009	.007	.011	-.005	-.002
Switzerland	2.02	.003	.002	.004	-.043	-.024
Turkey	1.98	.047	.034	.038	-.053	-.038
Ukraine	4.38	.105	.054	.069	-.045	-.038
United Kingdom	2.12	.015	.01	.014	-.003	-.001

Table A-74: Equivalent Variation Willingness-to-Pay (Share of GDP) Accounting for Economic Growth and Adaptation Costs and Benefits - Western Pacific and Oceania

Country	Projected GDP Per-Capita 2080 / Present	Ag GDP Share Baseline	Ag GDP Share 2080 Baseline	Ag GDP Share 2080 Counter-factual	EV WTP Losses from Present Baseline	EV WTP Losses from 2080 Baseline
Australia	1.5	.036	.03	.022	-.005	0
Fiji	3.79	.126	.08	.101	-.012	-.003
Indonesia	4.84	.112	.05	.057	-.018	-.012
Malaysia	2	.042	.031	.028	-.012	-.002
New Zealand	2	.078	.057	.08	.009	.003
Singapore	1.6	.007	.006	.005	-.009	-.003

Table A-75: Country-Level Panel Regression

	(1) log(GDP)	(2) Food Share of Imports	(3) Ag Share of GDP	(4) Ag Labor Share
KDD X 100	-0.0223	0.00638	0.0165	0.00483
	(-0.55)	(1.80)	(3.92)	(3.14)
GDD X 100	0.00251	-0.00191	-0.00165	-0.00113
	(0.44)	(-2.87)	(-1.53)	(-1.74)
Observations	7561	5775	5522	3718
Country FE	X	X	X	X
Year FE	X	X	X	X
Ag Labor Weights				

Notes: t-statistics in parentheses. Reported Driscoll and Kraay (1998) standard errors are robust to heteroskedasticity, spatial correlation, and autocorrelation of up to 5 lags. Results come from estimating Equation 24 with crop-area weighted growing and killing degree days. Data covers 164 countries from 1960-2012 with varying coverage by country and outcome variable. Economic data from all sources above are retrieved from the World Bank Databank.

Appendix G: Model Robustness

In this section, I evaluate the robustness of the counterfactual model simulations presented in Section 7 to three sets of different assumptions - an alternative specification for nonhomothetic consumer preferences, an alternative functional form to represent sector-country level productivity distributions, and a version of the model that allows for heterogeneous workers in each country.

Appendix G.1: Stone-Geary Preferences

I test that the model predictions are robust to the way nonhomothetic consumer preferences are specified by estimating a version of the model in which the representative agent in country k has the following generalized Stone-Geary preferences over the sectoral final goods in agriculture, manufacturing, and services:[54]

$$U(C_{ka}, C_{km}, C_{ks}) = \Bigg(\omega_a^{\frac{1}{\sigma}}(C_{ka} - \overline{C_{ka}})^{\frac{\sigma-1}{\sigma}} + \omega_m^{\frac{1}{\sigma}}(C_{km} - \overline{C_{km}})^{\frac{\sigma-1}{\sigma}} + \omega_s^{\frac{1}{\sigma}}(C_{ks} - \overline{C_{ks}})^{\frac{\sigma-1}{\sigma}}\Bigg)^{\frac{\sigma}{\sigma-1}} \tag{27}$$

This specification is ubiquitous in the literature on structural transformation and has the advantage of intuitively capturing subsistence requirements for food by specifying a level of consumption below which people cannot survive. However, the model fit to the data is much weaker with Stone-Geary preferences than with the primary nonhomothetic CES specification, as shown in Figure A-34.

Table A-76 shows that the results in this version of the model are very similar to the baseline specification. For the poorest quartile of the global population, climate change increases agriculture's share of the labor force by 2.8 percentage points, reduces GDP by 10.7 percentage points, reduces welfare (as captured by willingness-to-pay) by 7 percentage points, and raises food prices by 37%. These results are very similar to the results in the baseline specification.

Appendix G.2: Lognormal Productivity Distributions

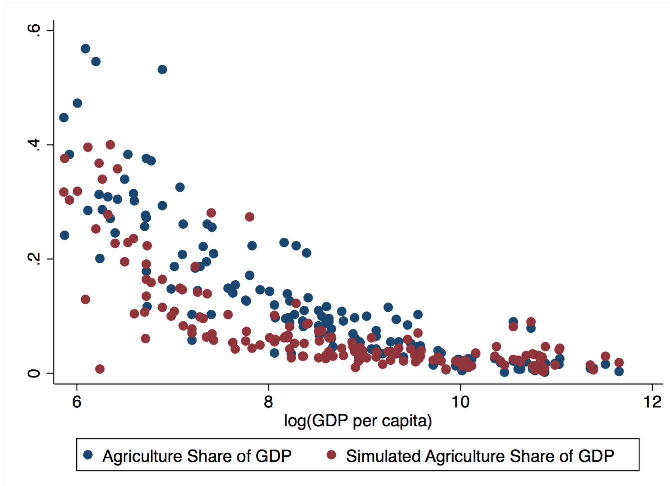
I estimate a version of the model with lognormal rather than Frechet sector-country productivity distributions to test robustness to functional form. In this specification the productivity draw, z_{ijk}, received by each intermediate goods producer is drawn from a lognormal distribution with sector-specific variance parameter φ_j and sector-country specific mean parameter Z_{jk}:

$$z_{ijk} \sim F_{jk} \text{ where } F_{jk}(z_i) = \Phi\left(\frac{(ln(x) - Z}{\varphi}\right)$$

I estimate φ_j to match the standard deviation of the productivity distributions in the

[54]The consumption parameter estimates for this version of the model are $\sigma = 0.89$, $\omega_a = 0.020$, $\omega_m = 0.141$, $\omega_s = 0.839$, $\overline{C_a} = 75.5$.

Figure A-34: Agriculture Share of GDP - Data vs. Simulation
Stone-Geary Specification



Notes: Graph shows the fit of simulated agriculture share of GDP to data from the World Bank with an alternative model specification using Stone-Geary preferences over sectoral consumption. The best fit with Stone-Geary preferences has an R^2 of only 0.43 and dramatically underpredicts the agriculture share in middle-income countries especially. In contrast, the chosen nonhomothetic CES preferences from Comin, Lashkari and Mestieri (2015) explain over 60% of the variation.

Table A-76: Climate Change Counterfactual Summary
Alternative Model Assumptions

Country	Δ Ag Labor Share	Δ GDP	Willingness to Pay	Δ Food Prices
Baseline				
World	.005	-.021	-.017	.223
Poorest Quartile	.028	-.126	-.088	.377
Lognormal Productivity				
World	.005	-.023	-.018	.209
Poorest Quartile	.022	-.131	-.09	.338
Stone-Geary Preferences				
World	.003	-.018	-.015	.219
Poorest Quartile	.028	-.107	-.07	.371

Frechet case, which yields estimates of φ_a = 0.337 and $\varphi_m = 0.398$. I estimate Z_{jk} to match both the ratio of value-added per worker across sectors and the overall level of value-added per worker in each country, as in the Frechet case.

Table A-76 shows that the results with lognormal productivity distributions are very similar to the baseline specification, with slightly larger declines in GDP and welfare, and slightly rises changes in food prices and agricultural labor shares in low-income countries.

Appendix G.3: Heterogeneous Workers

The baseline model makes the limiting assumption that each country contains a population of representative agents that each receive the same wage. In practice, we observe that wages differ substantially across sectors. Agricultural workers have lower wages than non-agricultural workers in most parts of the world, and especially so in poor countries.

In this section, I specify a version of the model with heterogeneous worker skill levels and explore how this extension affects the primary comparative statics of interest in the paper.[55] While an alternative model specification with adjustment costs that impede moving across sectors could also replicate the pattern in the macro data, recent empirical evidence points to worker heterogeneity as the central force underlying sectoral wage differences. In particular, Hicks, Kleemans, Li and Miguel (2017) find that workers experience only small gains in wages by moving from agriculture to non-agriculture when controlling for individual-level fixed effects. This suggests that low wages in agriculture stem from the different characteristics of the people working in that sector, rather than from barriers that prevent them from realizing large productivity and wage gains from a potential move into non-agricultural sectors.

In the version of the model with worker heterogeneity I start by assuming that each country has a fixed endowment of high-skill and low-skill workers, $\overline{L_H}$ and $\overline{L_L}$. Intermediate goods producers in each of the three sectors employ workers of both types and have sector-specific CRS production functions with varying skill-intensity (for simplicity I assume that manufacturing and services have the same skill-intensity):

$$\begin{gathered} Y_{ia} = z_{ia} l_{Hia}^{\beta} l_{Lia}^{1-\beta} \\ Y_{im} = z_{im} l_{Him}^{\alpha} l_{Lim}^{1-\alpha} \\ Y_{is} = z_{is} l_{His}^{\alpha} l_{Lis}^{1-\alpha} \\ \alpha > \beta \end{gathered} \tag{28}$$

Manufacturing and services are more high-skill intensive than agriculture, as reflected by the high-skill labor production elasticities $\alpha > \beta$. Solving the firm's problem gives the following optimal ratio of high-skill and low-skill workers employed in each sector as a function of the production elasticities and relative wages:

[55] Note that I do not estimate this version of the model because the simplified framework with two types of workers does not straightforwardly correspond to the data. In addition, it is not obvious how to estimate production elasticities by sector even if high-skill and low-skill workers were well-defined in practice.

$$\frac{L_{Hm}}{L_{Lm}} = \frac{\alpha}{1-\alpha}\left(\frac{w_L}{w_H}\right)$$
$$\frac{L_{Ha}}{L_{La}} = \frac{\beta}{1-\beta}\left(\frac{w_L}{w_H}\right)$$

With $\alpha > \beta$, these conditions imply that manufacturing and services firms will employ a higher share of high-skill workers than agricultural firms for any set of relative wages. The relative wage will adjust to satisfy both these conditions as well as the labor market clearing conditions in both sectors (total employment by skill type across the three sectors must add up to the country-level endowment by skill type) such that wages respond both to productivity and to the relative scarcity of each type of worker.

This version of the model leaves several predictions of the baseline specification unchanged, and makes two distinct predictions worth highlighting. The predictions of the baseline model that carry through in this extension concern the basic dynamics of sectoral reallocation in response to a productivity shock. As in the baseline model, a decline in agricultural productivity (Z_a falls) will raise the marginal cost of production for firms in agriculture, forcing them to raise prices in a competitive market. The variety-level increases in p_a will raise the corresponding aggregate price index for the final good in agriculture, P_a. The nonhomothetic consumer preferences remain as in the baseline specification, so Equation 22 governing the expenditure share in agriculture will continue to dictate that X_{ak} rises in response to the rise in P_a and the decline in real wages associated with the productivity shock. As in the baseline model, Equation 23 shows that agriculture's share of employment will rise with the expenditure share if the response of net exports to the change in comparative advantage is not sufficiently large. Thus, the competing forces of subsistence food requirements and international trade that govern the primary sectoral reallocation comparative statics are qualitatively robust to the extension with worker heterogeneity.

The model extension adds two dimensions of richness to our understanding of sectoral reallocation following a productivity shock in agriculture - more information about the distributional consequences of climate change and a more nuanced representation of comparative advantage. Incorporating heterogeneous workers into the model allows me to examine the distributional consequences of climate change within, in addition to across, countries. On this point, the model predicts that the relative wage of low-skill workers to high-skill workers rises with the revenue share of agriculture.[56] Thus, the 'food problem'

[56]The outline of the proof of this statement is as follows. In a perfectly competitive market with low-skill and high-skill workers as the only inputs to production, each sector's revenues are split between their workers according to their Cobb-Douglas production elasticities. So total income for each category is given by:

$$w_L\overline{L_L} = (1-\beta)R_a + (1-\alpha)R_m + (1-\alpha)R_s$$
$$w_H\overline{L_H} = \beta R_a + \alpha R_m + \alpha R_s$$

Consider a 1% increase in the revenue share of agriculture, r_a, and a 1% decline in the revenue share of manufacturing, r_m. The change in low-skill share of total income is given by $\alpha-\beta$ and the change in the high-skill share of total income is given by $\beta-\alpha$. With $\alpha > \beta$ the low-skill share of total income actually works to partially insulate farmers from the welfare costs of declining agricultural productivity. Intuitively, inelastic demand for the sectoral output good causes a strong response of the output price that raises the relative wages of the low-skill workers disproportionately employed in that sector. So while the relationship between greater openness to international trade, sectoral reallocation, and aggregate productivity remains similar in the case of heterogeneous workers, the extended model suggests that the adaptation gains from trade will likely be smaller for agricultural and other low-skill workers if trade moves domestic production away from that sector.

The second insight of the model with heterogeneous workers is that comparative advantage depends not only on the relative aggregate productivities in each sector, but also on the relative scarcity of high-skill and low-skill workers. Burstein and Vogel (2017) use a very similar model to specify a generalized definition of comparative advantage that incorporates both these Ricardian and Heckscher-Ohlin forces. In this framework, comparative advantage evolves endogenously with sectoral reallocation as relative wages shift with labor demand. Movement into (away from) agriculture raises (lowers) the relative wage of low-skill workers and shifts comparative advantage further toward (away from) manufacturing. For the primary climate change counterfactuals of interest in the paper, this additional channel would have the effect of attenuating the degree of sectoral reallocation in both directions. If the 'food problem' shifts production toward agriculture when its productivity falls, the resulting increase in the relative wage of low-skill workers pushes comparative advantage further toward manufacturing and endogenously strengthens the importance of the trade response pulling labor away from agriculture. Similarly, in the case of relatively free trade, production moving away from agriculture would reduce the relative wage of low-skill workers and endogenously dampen the movement of comparative advantage away from agriculture.

Overall, extending the model to represent workers of heterogeneous skill type leaves the fundamental predictions about climate change and sectoral reallocation unchanged, but sheds additional light on the forces underlying comparative advantage and the distributional consequences of climate change.

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rises. Since the total number of low-skill and high-skill workers is fixed, $\frac{w_L}{w_H}$ also rises.