Food Policy in a Warming World

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Abstract

This paper studies how governments intervene in agricultural markets to reshape the economic consequences of climate extremes. We construct a global dataset of agricultural policies and extreme heat exposure by country and crop since 1980. Extreme heat shocks to domestic production lead to policies that assist consumers by lowering domestic food prices. This effect is persistent, primarily implemented via border policies, and stronger during election years. Shocks to foreign production induce the opposite response: policies that assist producers by raising prices. These findings can be rationalized by a model in which governments use agricultural policy to redistribute among domestic interest groups. Our estimates imply that policy responses stabilize prices in shocked markets, reducing losses to domestic consumers by 21% while increasing those to domestic producers and foreign consumers by 172% and 32%. Policy responses have regressive consequences, disproportionately harming poor and heat-exposed countries, and may increase projected losses from climate change.

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1 Introduction

In March 2022, a heat wave in India reduced the country's wheat production by 11 million metric tons, or 10% of expected output (Beillard and Singh, 2022). On May 13, citing concerns that elevated prices threatened food security, the government announced a ban on wheat exports. While this policy had potential benefits for Indian consumers, it was controversial both in India and around the world. Farmer Ranbeer Singh Sirsa, quoted in the *New York Times* on May 14, decried the government's action: "If the price wants to go up, let it settle at the international price. Who are they trying to protect now, at the cost of farmers?" (Yasir and Kim, 2022). Ashok Gulati, former chairman of India's Commission for Agricultural Costs and Prices, concurred that the policy was "anti-farmer" and "painted a very sorry picture" of India's role in global commerce (India Today, 2022). Other critics focused on the global repercussions: on the policy's announcement, global wheat prices jumped 6%, exacerbating food security concerns in other countries (Lockett and Fildes, 2022). In 2023 alone, a similar story could be told for palm oil in Indonesia, rice in India and Myanmar, olives in Spain and Turkey, onions in Kenya and Tanzania, and potatoes and tomatoes in Morocco (Ghosal et al., 2023).

These examples have three ingredients that are increasingly common in a warming world. First, extreme heat is dramatically disrupting global agricultural production. Second, governments may not be passive observers and instead might react with policy interventions that balance different stakeholders' interests. Third, these policy reactions may redistribute the economic burden of environmental shocks, both domestically and around the world, and potentially either mitigate or exacerbate overall economic losses.

This paper combines measurement and theory to study the interaction between climate conditions and agricultural policy. In particular, we ask: does policy systematically respond to climate extremes? If so, how and why? And what are the implications for global adaptation to a warming world?

To study these questions empirically, we compile a global data set of temperature extremes and agricultural policy interventions since 1980. We measure annual exposure to extreme temperatures for every country-crop pair, combining gridded, global data on daily temperature realizations from the ERA5 dataset (Muñoz Sabater et al., 2021) with expert-elicited estimates of temperature tolerances for individual plant species. Our main empirical strategy exploits the differential exposure of country-crop pairs to exogenous variation in extreme heat over time. We validate that our measure of extreme heat reduces crop-specific yields in international panel data.

We measure agricultural policy interventions using data from the World Bank's Distortions to Agricultural Incentives project (Anderson and Valenzuela, 2008). This database reports the "nominal rate of assistance" (NRA), which measures percent distortions of domestic prices from international prices, as driven by policy interventions. The database covers 80 agricultural products and 81 countries, covering about 85% of global agricultural production (Anderson et al., 2013). The NRA is an appealing measure for our study because it takes into account multiple policy instruments, including border taxes, quantity restrictions, and domestic subsidies. We also use the specific components of the summary NRA measure, as well as measures of tariffs from the United Nations' Trade Analysis Information System (TRAINS) database and of other policy interventions from the Global Trade Alert (GTA) database, to further differentiate between policy levers and to validate our findings with independently collected data.

First, we document that extreme heat exposure systematically induces policy interventions that assist consumers by lowering domestic prices. These effects are particularly large for economically important staple crops. Moving from the first to fourth quartile of extreme heat exposure for staple crops induces a 30 percentage point change in the nominal rate of assistance. That is, a country with no distortion initially would implement a 30% domestic consumer subsidy. Decomposing this result across different policy tools, we find that governments respond primarily through border policies. We find no effects on agricultural input policies (e.g., fertilizer subsidies) and much weaker effects on non-border, output-based policies (e.g., agricultural buybacks). We then replicate our findings in independently collected data on tariffs and export restrictions. Consistent with our baseline results, domestic heat shocks lead to tariff reductions for *net importing* markets and to export restrictions for *net exporting* markets. While all countries respond to domestic shocks with consumer support, the policy tools they use depend on their precise circumstances.

Second, we investigate how extreme heat exposure in foreign markets affects agricultural policy. We measure external shocks with two strategies: a leave-one-out average of shocks to all global producers and a country-specific measure that weights shocks by pre-period import and export linkages. With both approaches, we find that foreign extreme heat shocks lead to a more producer-oriented policy at home. Unconditional increases in global prices also lead to pro-producer policy, and this effect is larger and more precisely estimated when we instrument for international prices with extreme heat shocks. Thus, a food security threat that originates overseas has precisely the opposite effect as one that originates domestically. This finding is inconsistent with the hypothesis that governments' singular goal is to reduce price fluctuations for consumers, regardless of their origins. It also contradicts narratives of food policy "contagion" and "multiplier effects" in case studies of global food trade disruptions (e.g., Ghosal et al., 2023). Explaining the opposite policy responses to domestic and foreign supply disruptions is a key novelty of our theoretical model, which we describe below.

Third, we investigate the dynamics of policy responses to extreme heat shocks. Policy does not anticipate future changes in extreme heat, but persists for up to three years after the original shock. Motivated by this finding, we also study how long-run changes in climate affect long-run policy stances. In principle, long-run responses could be weaker than short-run responses if there is mean reversion in policy or adaptation in production and trade (Dell et al., 2012; Burke and Emerick, 2016). However, we find decadal-frequency effects that are consistent with, and slightly larger than, our baseline annual-frequency estimates. Governments respond not only to short-run weather fluctuations, but also to longer-run climate trends.

Finally, we consider mechanisms by studying heterogeneity in our baseline estimates of how extreme heat affects policy. We first examine short-term political incentives, treating the timing of elections as within-country variation in the salience of constituent demands.[1] In the lead-up to elections, we estimate effects that are roughly four times as large as our baseline estimates. Short-term political incentives shape policy responses to extreme heat shocks and thus their distributional consequences. Second, we investigate the mitigating effect of fiscal constraints, and we find muted effects when countries' debt-to-GDP ratio is high. When countries lack fiscal flexibility, they are less likely to intervene in response to shocks. Third, we investigate differences based on proxies for country-level economic development and political institutions. We find little evidence of heterogeneity along these margins. Rich and poor nations and democratic and autocratic regimes all seem to face strong incentives to assist consumers when the supply of staple foods is threatened. But we do find some evidence of stronger responses in less agricultural countries—those that are more urban and those that import a large share of their food—and in products that are disproportionately consumed by the poor.

We rationalize this collection of results with a model of optimal government policy

[1] This strategy builds on the idea that "electoral cycles" affect political behavior (see e.g., Nordhaus, 1975; Alesina and Roubini, 1992; Akhmedov and Zhuravskaya, 2004; Balboni et al., 2021)

with redistributive concerns, in the tradition of Grossman and Helpman (1994), Goldberg and Maggi (1999), and Maggi and Rodríguez-Clare (2000). A government sets a border tax to maximize a weighted sum of consumer surplus, producer surplus, and government revenue. If the government is sufficiently *redistribution-focused*—as defined by a condition that we derive on the extent of government concern for consumers and producers compared to revenue—then optimal policy responds to domestic supply shocks with pro-consumer policy interventions. In this case, the government's main consideration is that reduced domestic supply shifts the burden of lowering prices away from domestic producers and toward foreign producers, on whom the government places no weight. The same logic implies that the government would intervene to raise domestic prices and assist producers in response to a shock that reduces foreign production or raises foreign demand.

Our model can rationalize our full set of empirical findings, including those that may seem surprising at first blush. We find that, driven by political incentives, governments assist consumers when an adverse domestic shock threatens food security, but they do the opposite when an adverse foreign shock threatens food security. These findings are not consistent with a model predicated solely on meeting acute subsistence needs or ensuring stable prices. Moreover, our model reconciles the vast heterogeneity in baseline policy stances around the world with the consistent pro-consumer responses that follow domestic shocks. And our model rationalizes that redistributive and fiscal considerations, as proxied by elections and debt burdens, shift governments' incentives to intervene.

Finally, we use the model to quantify how policy responses shape the aggregate and distributional consequences of extreme heat shocks in general equilibrium. We calibrate the model to match our empirical estimates for climate damages and policy responses, as well as external estimates of the elasticities of supply and demand for each market. In sample, government intervention in shocked markets dampens price increases by 18% relative to a counterfactual in which policy is held fixed. Governments shield domestic consumers by offloading losses onto domestic producers and foreign consumers, whose losses are increased by 172% and 36%, respectively. Because policy adjustments occur in an already second-best world, they sometimes lessen and sometimes amplify pre-existing distortions. The net effect is that the equilibrium with responsive policy is *regressive* compared to the equilibrium with fixed policy: policies tend to increase deadweight loss and reduce total welfare in the poorest markets and in those that are most negatively affected by extreme heat shocks. This result is consistent with the intuition that lower-income countries subsidize food consumption and tax agriculture at baseline (Anderson et al., 2013), are hit frequently by temperature extremes, and respond to these shocks by further subsidizing consumption. Finally, we simulate the model under projected extreme heat exposure for the decade 2091-2100. We find that responsive policy exacerbates the overall agricultural welfare loss from climate change by 8%. The reason is that climate change is predicted to have greater incidence in markets that currently already subsidize consumers. Policy responses then induce further consumer assistance, amplifying policy distortions and increasing deadweight loss.

Our main contribution is to show that agricultural policy responds to extreme heat shocks, thereby shaping their aggregate and distributional effects. We build on existing work studying distortions to agricultural incentives. Others have documented these distortions around the world (Krueger et al., 1988; Johnson, 1991; Anderson, 2009; Anderson et al., 2013) and argued that they are driven by politicians' desire to redistribute between the producers and consumers of food (Barrett, 2013; Bates, 2014). We depart from existing work by focusing on responses to exogenous exposure to temperature extremes, rather than political trends or static cross-country differences.[2] We show that policy responses reshape and, in some cases, worsen the economic impacts of extreme temperatures.

A large literature quantifies the impacts of extreme heat on agricultural production (see, e.g., Lobell and Field, 2007; Schlenker and Roberts, 2009; Lobell et al., 2011). Costinot et al. (2016) study global adaptation via trade and how it might reduce projected welfare losses from climate change. Others study how trade interacts with other mechanisms, which include crop switching (Baldos et al., 2019; Hultgren et al., 2022), land and water use (Carleton et al., 2022), sectoral reallocation (Rudik et al., 2022; Nath, 2023), migration (Cruz and Rossi-Hansberg, 2023; Conte, 2024), technology (Farrokhi and Pellegrina, 2023), and regulation (Shapiro, 2021; Farrokhi and Lashkaripour, 2024; Hsiao, 2025). Each treats domestic policy distortions as fixed. We show that policy itself responds to environmental changes and that these policy responses can create frictions to adaptation.[3] We discuss implications for global resilience to climate change.

2 Data and Measurement

We construct a panel dataset on agricultural policy, extreme heat shocks, and other agricultural, political, and economic outcomes.

[2] Bastos et al. (2013) and Amodio et al. (2024) investigate how rainfall shortages affect agricultural tariffs. Their findings that rainfall shortages induce tariff reductions are consistent with our first result.

[3] Similarly, Hsiao (2023) shows that endogenous government intervention complicates adaptation to rising sea levels by inducing potential moral hazard. Hsiao (2024) takes on distributional consequences.

2.1 Agricultural Policy

We measure distortions in agricultural markets with data from the World Bank's "Distortions to Agricultural Incentives" (DAI) project (Anderson and Valenzuela, 2008; Anderson, 2009). This dataset reports price distortions for 80 agricultural products and 82 countries from 1955 to 2011 (in an unbalanced panel). The sample accounts for over 85% of agricultural production and employment globally, as well as within each of Africa, Asia, Latin America, and the OECD (Anderson et al., 2013). In sensitivity analysis, we also use NRA data from the Ag-Incentives project, an unofficial continuation of the DAI Project.

The key statistic of interest is the *nominal rate of assistance* (NRA). Conceptually, the NRA measures the extent to which policy intervention drives a wedge between domestic producer prices and prevailing "free market" international prices. That is, for crop k in country ℓ at time t,

$$\mathrm{NRA}_{\ell kt} = \frac{p_{\ell kt} - p^I_{kt}}{p^I_{kt}} \tag{2.1}$$

where $p_{\ell kt}$ is the distorted, domestic price per unit of production, and p^I_{kt} is the undistorted free-market international price, which is unobserved. Following previous work, we say that positive values of the NRA correspond to policies of *producer assistance*, in the sense that they elevate domestic prices above free-market levels. We say that negative values correspond to *consumer assistance* for the opposite reason.

In practice, the NRA is computed by estimating the ratio of total assistance paid to producers (in dollars) relative to the total value of production driven by policy interventions. This involves compiling granular price and output data along with detailed qualitative reports about policy changes (Anderson, 2009), including market price support, payments to producers based on output, payments to producers based on inputs, and payments to producers based on other indicators (e.g., area cultivated). The goal is to paint as complete a picture as possible of distortions affecting agricultural markets around the world, and in turn their implied effects on prices. Recent studies in economics on agricultural misallocation (Adamopoulos and Restuccia, 2014) and agricultural trade and resource use (Carleton et al., 2022), as well as work in political science on urban-rural policy conflict (Wallace, 2013; Bates and Block, 2013), have treated the NRA as the most comprehensive available data source on agricultural policy interventions.

For our specific research question, the NRA data have two key advantages relative to other measures of agricultural policy. First, they capture policy instruments other than border taxes. The NRA measure accounts for quantity restrictions in terms of the induced price wedge, and so it captures non-tariff policy responses like our motivating example of India's export ban in 2022. Similarly, the NRA measure accounts for indirect assistance through input price distortions or exchange rate manipulation. It therefore captures agricultural assistance that substitutes for direct export subsidies, which are prohibited under World Trade Organization rules. Second, the NRA measure can capture temporary variation in trade policy that is not set by legislation. Together, these features allow us to observe relevant policy variation and to account for how governments use different instruments as complements or substitutes for one another.

Additional Data Sources. To investigate how governments use specific policy tools and to validate our results using alternative, independently collected data, we also assemble data on tariffs and export restrictions. We measure crop-specific tariffs using the United Nations' Trade Analysis Information System (TRAINS) database by linking all relevant Harmonized System (HS) codes in the TRAINS data to individual crops in our data set. These data reduce our reliance on the modeling and imputation decisions of a single data source, although at the cost of capturing only one dimension of policy. We also compile data on all import and export restrictions that affect agricultural commodities from the Global Trade Alert (GTA) database. The GTA data, which aim for comprehensive coverage since 2008, lists all sector-specific policy interventions broken down by industry (HS code) and policy type. We identify all policy activity affecting the HS codes corresponding to crops in our analysis, and we directly measure changes in the number of export- and import-restricting policies at the crop-by-country-pair level.[4]

2.2 Extreme Heat Exposure

We measure agricultural shocks by constructing a global dataset of crop-level exposure to extreme heat in each country and year. Our measure incorporates information about the global distribution of temperature extremes, the global geography of crop production, and crop-specific sensitivity to extreme heat. We can therefore exploit the fact that regions are differentially exposed to extreme heat and that, even in a given region, crops vary in their sensitivity to extreme heat exposure.

Data Inputs. We measure historical temperatures using the ERA5 database from the European Centre for Medium-Range Weather Forecasts (Muñoz Sabater et al., 2021).

[4] Export-restricting policies are those tagged as export bans, export quotas, export licensing requirements, export tariffs, export taxes, and export non-tariff barriers. Import-restricting policies include import bans, import licensing requirements, import quotas, import tariffs, and import non-tariff barriers.

This reanalysis data set combines weather observations from around the world with a model to generate gridded (0.25-by-0.25 degrees), hour-by-hour measurements since 1979.

We measure the global geography of agricultural production with data from the *Earthstat* database of Monfreda et al. (2008). These data were created by combining national-, state-, and county-level census data with crop-specific potential yield data to construct a 5-by-5 minute grid of the area devoted to each crop circa 2000.

We measure crop-specific temperature sensitivity with data from the United Nations Food and Agriculture Organization's *EcoCrop* database. The EcoCrop data provide information about growing conditions for 2,500 agriculturally important plants, including tolerance ranges for temperature and rainfall. The data are compiled from expert surveys and textbooks. The key piece of information for our analysis is the reported upper temperature threshold for optimal growing.[5]

Measurement. We measure crop-specific extreme heat exposure for each country-crop combination as the average exposure to extreme temperatures, in degree-days, on land cultivating a given crop. Prior work has shown that extreme heat exposure is the quantitatively most important way in which temperature affects output (e.g., Schlenker and Roberts, 2009) and that temperature differentially affects productivity across crops (Ritchie and Nesmith, 1991).[6] Following Moscona and Sastry (2023), we partition each country ℓ into grid cells $c \in \ell$, and for each country ℓ, crop k, and year t we compute

$$\text{ExtremeHeat}_{\ell kt} = \sum_{c \in \ell} \frac{\text{Area}_{ck}}{\sum_{c' \in \ell} \text{Area}_{c'k}} \cdot \text{DegreeDays}_{ct}(T_k^{max}) \tag{2.2}$$

$\text{DegreeDays}_{ct}(x)$ returns total degree days in excess of threshold x in cell c at time t. T_k^{max} is the maximum optimal growing temperature for crop k from EcoCrop. Area_{ck} is the area growing crop k in cell c from the EarthStat data.

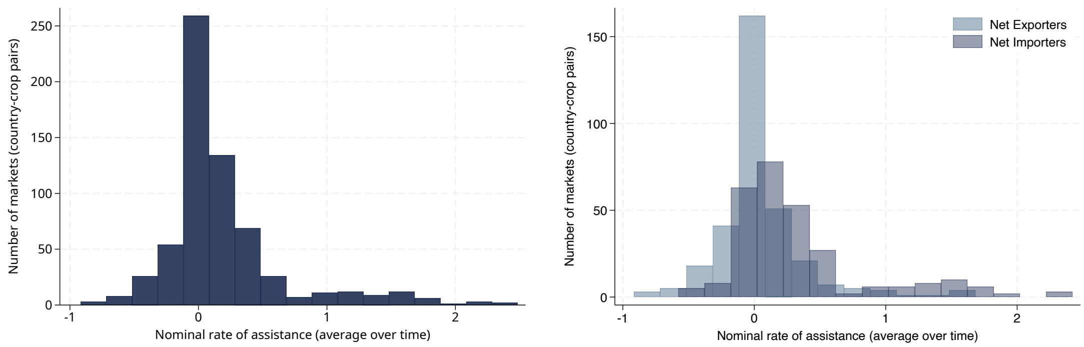
This method extends existing work on the impact of rising temperatures on global agricultural production (Lobell and Field, 2007; Lobell et al., 2011). Our contribution is to incorporate temperature extremes rather than averages, a larger set of crops, and crop-specific measures of temperature sensitivity. These data may be of independent interest

[5] This database has been used in agronomics and climate science to estimate crop-specific effects of climate change (e.g., Ramirez-Villegas et al., 2013; Hummel et al., 2018) and in economics to measure exposure to crop-specific adverse conditions (Moscona and Sastry, 2023; Hsiao, 2025).

[6] Using panel data from the United States, Moscona and Sastry (2023) document that this crop-specific extreme heat exposure measure predicts adverse agricultural outcomes and that it outperforms comparable measures that do not account for crop-specific tolerance.

Figure 1: Agricultural Distortions Across Markets

(a) All Markets **(b)** Exporting Versus Importing Markets



This figure displays the distribution of the nominal rate of assistance across markets (country-crop pairs), averaged across years and time periods. We truncate the distribution at the 99th percentile. Panel A shows the distribution across all 648 markets in the sample. Panel B splits the distribution based on trade balance (summed over our sample) into 341 exporting markets and 301 importing markets.

for research on climate change and agricultural productivity.

2.3 Production, Trade, Elections, and Debt

We compile data on production, producer prices, exports, and imports at the crop-country-year level from the United Nations (UN) Food and Agriculture Organization (FAO) FAOStat database. Data on election years in our sample period are from the Database of Political Institutions (DPI) first introduced by Beck et al. (2001). The database covers election information and regime characteristics for 180 countries from 1975 to 2020. We compile data on government debt from the International Monetary Fund (IMF) Global Debt Database, and we compute central government debt as a share of GDP at the country-year level. To measure crop shares of consumption and income across income groups within each country, we use data from the World Bank Household Impacts of Tariffs (HIT) database, which compiles household-level expenditures and income source information derived from a broad range of representative surveys. All remaining country-level data are from the World Development Indicators (WDI) database.

2.4 Summarizing and Visualizing the Data

Agricultural policies vary substantially around the world. Figure 1 shows the distribution of the NRA across the 648 markets (country-crop pairs) in our sample, averaged across years. We observe large magnitudes: 50% of all markets have a price wedge larger than

15% in absolute value, and 10% of markets have a price wedge larger than 80%. These patterns hold for both net exporting and net importing markets in our sample, although perhaps especially so for net importers. Focusing on staple crops, Figure A.1 maps average NRA from 2001-2010 for all countries with available data for maize, wheat, and rice.

Our interest is in the substantial variation over time in agricultural assistance. Figure A.2 shows changes in the nominal rate of assistance between the 2000s and the 1980s for maize, wheat, and rice. At a glance, this figure is consistent with the documented trend toward lessening producer protection in Europe and the Americas and lessening food subsidies in sub-Saharan Africa, South Asia, and East Asia. But there are substantial differences in these changes both across countries and across crops in the same country. For example, the United States reduces assistance for wheat, while India increases it, and India increases assistance for wheat but decreases assistance for maize.

Extreme heat also has heterogeneous incidence. Figure A.3 illustrates changes in $\text{ExtremeHeat}_{\ell k}$ between the 1980s and the 2000s for maize, wheat, and rice. While extreme heat exposure has increased in most countries for all three crops, there is substantial variation in the magnitude of the effect. For example, Brazil is in the third quartile for maize, second quartile for wheat, and fourth quartile for rice. Throughout our analysis, we exploit variation in extreme heat exposure both within crops and within countries, as highlighted by Figure A.3. We can therefore absorb any country-specific or crop-specific trends that may spuriously co-vary with adverse weather conditions.

We highlight this identifying variation by zooming in on staple crops in India. Figure 2 shows the evolution of extreme heat exposure and NRA for Indian maize, wheat, and rice. While extreme heat exposure has increased over time for all three crops, there remain large fluctuations from year to year that we will use for identification. Both the level of extreme exposure and the pattern over time also vary substantially across these three major crops in the same country.

2.5 Validation: Extreme Heat Lowers Crop Yields

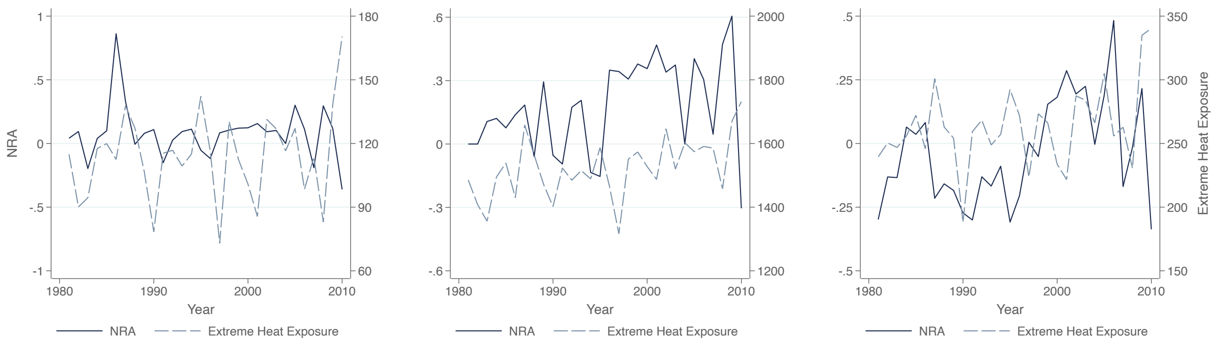
Before turning to the main results, we show that extreme heat exposure adversely affects agricultural productivity. We estimate the following regression:

$$\log(\text{yield}_{\ell kt}) = f(\text{ExtremeHeat}_{\ell kt}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \varepsilon_{\ell kt} \tag{2.3}$$

where $\text{yield}_{\ell kt}$ is output per unit of land for crop k in country ℓ and year t. We include all possible two-way fixed effects. $\text{ExtremeHeat}_{\ell kt}$ is defined in Equation 2.2, and we estimate

Figure 2: Extreme Heat and Policy for India

(a) Maize **(b)** Wheat **(c)** Rice



This figure displays extreme heat exposure and NRA over time in India for maize, wheat, and rice. The NRA is plotted on the left y-axis (dark blue solid line) and extreme heat exposure is plotted on the right y-axis (light blue dashed line).

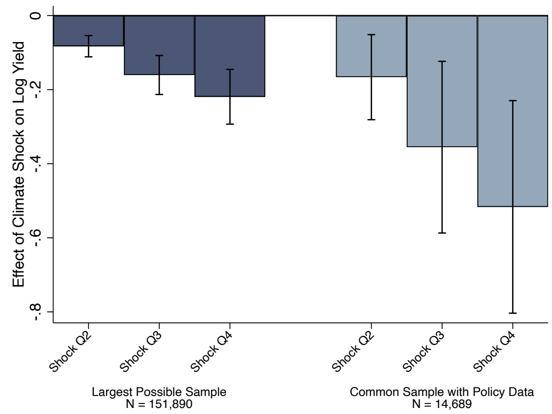
function f that encodes effects by quartile of $\text{ExtremeHeat}_{\ell kt}$. The two-way fixed effects mean that our estimates only exploit variation across crop within country-years. As a result, they are not driven by country- or crop-specific trends, or by differences in crop specialization across countries.

We estimate a large, negative effect of extreme heat exposure on yields (Figure 3). Compared to the the bottom extreme heat quartile, yields in the top extreme heat quartile are over 20% lower. Our estimates are larger when we restrict attention to the subsample of observations for which we have policy data. These estimates validate that our measure of extreme heat exposure has substantial negative effects on agricultural productivity.

3 Empirical Results

This section presents our main empirical findings. First, extreme heat shocks to local production lead to large shifts in agricultural policy that favor domestic consumers. Second, these effects are driven by policies at the border. Third, foreign shocks that put upward pressure on global food prices lead to producer assistance. Fourth, policy changes do not anticipate shocks but do persist for several years, and also respond to longer-run changes in the climate. Fifth, policy responses respond to short-term political and fiscal incentives, but seem broadly similar for countries that are more or less developed or democratic.

Figure 3: Extreme Heat Reduces Agricultural Yields



This figure shows the relationship between extreme heat exposure and log crop yields. The model is Equation 2.3, with f parametrized by indicators for quartiles of extreme heat (the first is the excluded category). The unit of observation is a country-crop-year, and all possible two-way fixed effects are included. Each set of bars corresponds to the estimates from a single regression. The left set of bars ("Largest Possible Sample") is from a regression that includes the full sample for which we measure the temperature shock and production. The right set of bars ("Common Sample with Policy Data") restricts the sample to the crop-country-year triplets for which we have data on the nominal rate of assistance. We report 90% confidence intervals.

3.1 Local Extreme Heat Leads to Pro-Consumer Policy

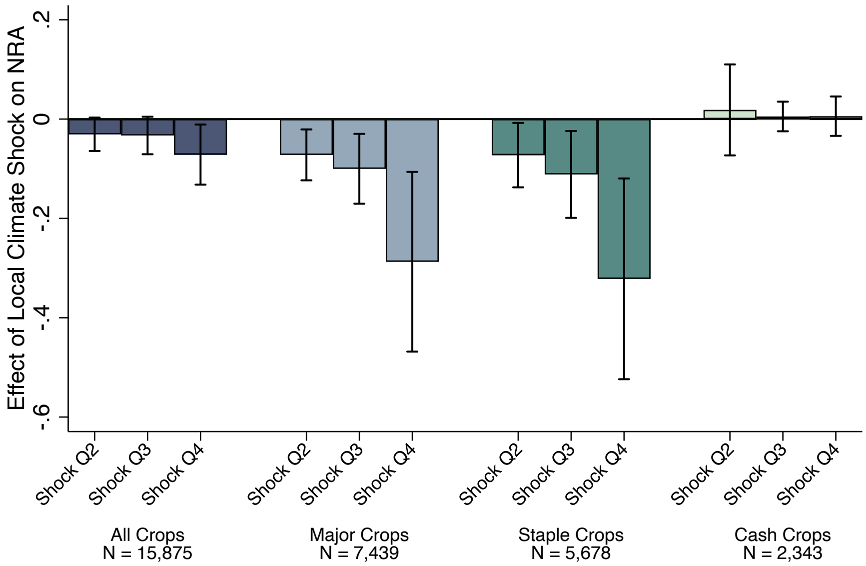
We first investigate the relationship between local extreme heat exposure and crop-specific policy. Our main estimating equation is

$$\text{NRA}_{\ell kt} = g(\text{ExtremeHeat}_{\ell kt}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \varepsilon_{\ell kt} \tag{3.1}$$

where $\text{NRA}_{\ell kt}$ is a measure of crop-specific policy for crop k in country ℓ and year t. We estimate non-parametric function g with indicators for each of the four quartiles of $\text{ExtremeHeat}_{\ell kt}$. All specifications include the full set of two-way fixed effects, fully absorbing any differences in baseline specialization across countries, as well as country-specific and crop-specific trends. We report our findings in Figure 4. Each set of three bars corresponds to estimates from a separate regression, and the coefficients are effects relative to the left-out category of first-quartile exposure.

Our first finding is that extreme heat exposure induces consumer assistance on our full sample of countries and crops (dark-blue bars). Experiencing fourth-quartile compared to first-quartile extreme heat exposure reduces NRA by 0.072, corresponding to a 7.2% reduction in domestic prices relative to international prices. In our panel data, such a

Figure 4: Extreme Heat and Agricultural Policy



This figure shows the relationship between extreme heat exposure and the nominal rate of assistance (NRA). The model is Equation 3.1, with g parametrized by indicators for quartiles of Extreme Heat (the first is the excluded category). The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each set of three bars corresponds to estimates from a single regression, where the first quartile is the excluded category. The sample of crops included in each regression is noted below the x-axis. Standard errors are clustered by market and error bars are 90% confidence intervals.

change corresponds to 0.092 in-sample standard deviations of the NRA variable. The finding is consistent with our motivating example, in which India banned wheat exports following a national heatwave in 2022. This first result confirms that such policy reactions are systematic and quantitatively large relative to baseline variation in agricultural policy.

We next restrict attention to the ten most economically important crops identified by Costinot et al. (2016): bananas, cotton, maize, rice, soybeans, sugar, tomatoes, wheat, potatoes, and oil palm. Our estimates using this sub-sample (blue-grey bars) are substantially larger in magnitude: experiencing high extreme heat exposure reduces NRA by 29 percentage points or 0.37 in-sample standard deviations. Moreover, the fourth-quartile effect is substantially larger than the third-quartile effect ($p = 0.06$). This finding suggests that most extreme shocks may have a disproportionate effect on policy.

Finally, we compare effects for staple and cash crops.[7] We find large, negative effects

[7]The staple crops we include are maize, soybeans, rice, wheat, tomatoes, potatoes, and onions. The cash crops are cocoa, coffee, cotton, palm oil, sugar, and tobacco.

of extreme heat exposure on NRA for staple crops (dark-green bars). Quantitatively, these results are similar to our estimates for all major crops: high (compared to low) extreme heat exposure for staple crops reduces NRA by 32 percentage points or 0.41 standard deviations, and the fourth-quartile effect is statistically distinguishable from the third-quartile effect ($p < 0.01$). However, we find no statistically significant evidence that extreme heat exposure affects agricultural policy for cash crops (light-green bars). One possible explanation is that staple crops are more important in terms of income and consumption for households that the government prioritizes. By contrast, cash crops are a source of income for a smaller set of constituents and are consumed primarily by foreigners. The model of Section 4 will formalize potential drivers of these differences in policy response across products.

Together, these estimates suggest that exposure to extreme heat reduces NRA, leading to more consumer-oriented agricultural policy. The effects are particularly pronounced for staple crops and for the highest levels of exposure to extreme temperatures. Moreover, the effects are very similar if we exclude any decade from the sample period (Table A.1, Panels A-C), or if we use alternative data on NRA to extend the sample to the present (Panel D).[8] Thus, the findings are not driven by any particular climate or political event, and instead capture a systematic feature of policy making under environmental stress.

Country-Level Estimates and Cross-Crop Interactions. Our baseline estimates exploit variation in temperature and policy not only across countries and over time, but also across *crops* within the same country. The advantages to this approach are that (1) the country-crop-year is the level at which policy is set and thus the relevant unit for measuring extreme heat exposure, (2) there is substantial dynamic variation in both policy and extreme heat exposure across crops and within countries (Figures A.2 and A.3), and (3) the country-by-year fixed effects in our baseline specification fully absorb any country-level trends or shocks that might spuriously co-vary with policy or temperature. This is potentially important because of meaningful regional-specific time trends in assistance to agriculture (Anderson et al., 2013) and in planetary warming.

Nonetheless, we also estimate country-level effects to investigate how our crop-country-year estimates aggregate. Country-level estimates might exceed our baseline estimates if governments are more responsive to high overall exposure to extreme heat, rather than

[8]The extended series requires linking our main dataset with NRA measurement from the Ag-Incentives project. This is not the baseline specification due to differences in methodology between the two data sets. When we estimate a regression that includes both (Panel D), we include an Ag-Incentives indicator interacted with all two-way fixed effects to capture average differences due to methodology.

high exposure for a single crop, because overall exposure may be more burdensome for consumers. But country-level estimates might be smaller if politicians face a political budget that constrains their ability to change policy across multiple commodities simultaneously. Country-level estimates may also capture policy levers that are absorbed by the inclusion of country-year fixed effects, such as exchange rate manipulation.

We average our baseline data to the country-year level, focusing on the ten major crops from our baseline analysis and weighting each crop-country-year observation by average calorie-weighted production during the first decade of our sample period (1980-1989). We then estimate the following country-year analog of our baseline regression:

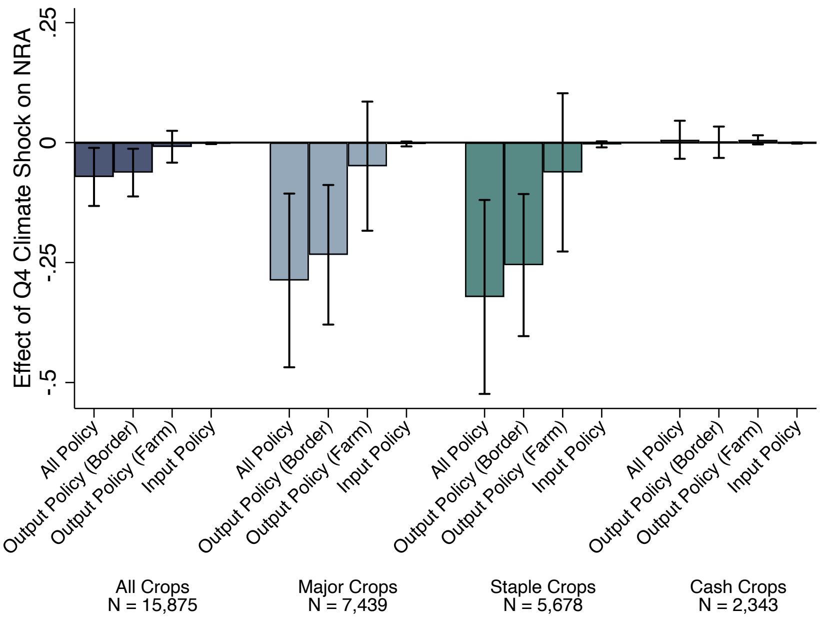
$$\text{NRA}_{\ell t} = g(\text{ExtremeHeat}_{\ell t}) + \gamma_{\ell} + \delta_t + \varepsilon_{\ell t} \tag{3.2}$$

We report our estimates in Table A.2. Country-level extreme heat exposure leads to a pro-consumer policy response (column 1). Consistent with our baseline estimates in Sections 3.2 and 3.4, the effects are driven by border-market policies, rather than output-market or input-market policies (columns 2-5), and the policy response persists in the year after the temperature shock takes place (Table A.2, Panel B). These estimates are quantitatively similar to the estimates from the country-crop-year specification, indicating that cross-crop interactions do not have large effects on average. We also reproduce our baseline estimates of Equation 3.1 without any fixed effects, then we add each set of fixed effects sequentially (Table A.3). While the specific set of controls affects precision, the coefficients are similar in magnitude across specifications. Our baseline estimates thus do not hinge on the exact source of temperature variation or spillovers across crops.

3.2 Governments Primarily Respond through Border Policies

We next exploit more granular data on specific types of policy to investigate exactly how governments intervene in agricultural markets. First, we estimate Equation 3.1 using each component of NRA as a separate dependent variable (Figure 5). For brevity, we only report the effect of the top quartile of extreme heat exposure. All components of policy respond to adverse shocks in a pro-consumer direction, indicating that our previous result for the overall rate of assistance does not mask partially offsetting policy changes. However, our results are primarily driven by output-related policies and, in particular, policies that affect prices at the border. By contrast, the effect is weaker for policies that affect output prices at the farm gate (e.g., price support) and absent for policies that affect agricultural inputs (e.g., fertilizer subsidies).

Figure 5: Effects of Extreme Heat on Different Policy Margins



This figure displays the relationship between extreme heat exposure and different components of the nominal rate of assistance. The model is Equation 3.1, with g parametrized by indicators for quartiles of Extreme Heat (the first is the excluded category). For concision, we report only the coefficient on the fourth quartile. Each bar is an estimate from a separate regression. Each group of four bars corresponds to a different sample of crops. Within each group, each bar corresponds to the indicated outcome. Standard errors are clustered by market and error bars are 90% confidence intervals.

We now more closely study how governments use trade policy to respond to climate shocks. In Panel A of Table 1, we study how the response of the nominal rate of assistance depends on countries' trade position by estimating versions of Equation 3.1 on different samples. We find negative effects of extreme heat shocks on the NRA, of similar magnitude to the baseline effect (column 1), for the subsamples of net importers (column 2) and net exporters (column 3). The effect is slightly larger for net importers but not statistically different. Both estimates lose some precision because of smaller sample sizes.

Next, we use independently collected data to study specific trade policy interventions. Panel B presents estimates of Equation 3.1 where the outcome is the tariff rate measured in the UN TRAINS database. Governments reduce tariffs in response to extreme heat shocks in the full sample (column 1), consistent with a desire to reduce domestic relative to international prices. The effect is substantially more pronounced—about double in absolute value—for net importers (column 2) compared to net exporters (column 3).

Table 1: Extreme Heat and Trade Policies

	(1) Full Sample	(2) Net Importers	(3) Net Exporters
Panel A: Dependent Variable is NRA			
Q4 Extreme Heat	-0.287	-0.331	-0.220
	(0.125)	(0.257)	(0.098)
Country-Year Fixed Effects	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes
R-Squared	0.770	0.751	0.648
Observations	7439	3919	2778
Panel B: Dependent Variable is Tariffs			
Q4 Extreme Heat	-0.057	-0.101	-0.050
	(0.028)	(0.045)	(0.024)
Country-Year Fixed Effects	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes
R-Squared	0.791	0.825	0.809
Observations	12461	6106	5934
Panel C: Dependent Variable is Net Export Restrictions (GTA)			
Q4 Extreme Heat	0.087	-0.063	0.162
	(0.049)	(0.058)	(0.045)
Country-Year Fixed Effects	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes
Country-Pair-Year Fixed Effects	Yes	Yes	Yes
R-Squared	0.428	0.438	0.423
Observations	101052	56779	35984

This table reports the relationship between extreme heat exposure and trade policy interventions. In Panels A and B, the model is a variant of Equation 3.1 and the outcome is at the country-crop-year level. The outcomes, respectively, are the nominal rate of assistance and the tariff rate measured in the UN TRAINS database. In Panel C, the model is Equation 3.3 and the outcome is the number of export restrictions net of the number of import restrictions recorded by Global Trade Alert at the country-pair-by-year level. In all cases, g is parametrized by indicators for quartiles of extreme heat. For brevity, we report only the coefficient on the fourth quartile. Column 1 corresponds to the largest possible sample of markets. Column 2 restricts the sample to markets that were net importers (on average) during our analysis period, and column 3 restricts the sample to markets that were net exporters during the analysis period. Standard errors are clustered by market.

Intuitively, a border tariff is more effective in net-importing markets because it applies to a larger share of domestic consumption in these markets.

In Panel C, we study the effect of extreme heat on trade restrictions measured in the Global Trade Alert dataset. Our estimating equation is

$$\text{NetExportRestrictions}_{\ell\ell' kt} = g(\text{ExtremeHeat}_{\ell t}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \xi_{\ell\ell' t} + \varepsilon_{\ell\ell' kt} \tag{3.3}$$

where ℓ and ℓ' denote acting and affected countries, the outcome is the count of export restrictions (net of the count of import restrictions) at the country-pair by crop by time level, and a new fixed effect at the country-pair by time level controls for background changes in the economic and geopolitical relationships between countries. Export restrictions increase in response to local extreme heat exposure (column 1) but, intuitively, these estimates are driven by net exporters (column 3) and not net importers (column 2). The results are similar for alternative parameterizations of the outcome, including using the (non-normalized) count of export-restricting policies (Figure A.6). These estimates again corroborate our main finding that governments respond to extreme heat shocks with pro-consumer policy. And they are consistent with the important role of export restrictions, as highlighted in our motivating example.

Together, these findings illustrate that all markets—regardless of their trade position—respond to domestic heat shocks with trade policy that limits price increases. The exact policy levers used in each market, however, depend on the market's trade position.

3.3 Foreign Extreme Heat Leads to Pro-Producer Policy

The previous section documents that local extreme heat shocks reduce NRA, leading to more consumer-oriented policy. But foreign shocks may also affect policy actions in an interconnected world. Ghosal et al. (2023) discuss the potential for "contagion of food restrictions," as countries react to restrictions by their trading partners. For example, "India banned shipments of some rice earlier this year, resulting in a shortfall of roughly a fifth of global exports. Neighboring Myanmar, the world's fifth-biggest rice supplier, responded by stopping some exports of the grain." That is, India and Myanmar both enact export restrictions following the Indian shock. These compounding policy responses could further exacerbate the impact of temperature shocks on global prices and trade. At the same time, these examples could represent unique cases that are not representative, or capture independent responses to correlated domestic shocks among trading partners.

Methods. We study this issue empirically with three strategies for measuring foreign shocks. First, we construct a global crop-level measure of extreme heat exposure. We calculate a "leave-one-out" average of crop-specific extreme heat exposure over grid cells in all countries (L) except the country in question:

$$\text{ForeignExtremeHeat}_{\ell kt} = \sum_{c \in L \setminus \ell} \frac{\text{Area}_{ck}}{\sum_{c' \in L \setminus \ell} \text{Area}_{c'k}} \cdot \text{DegreeDays}_{ct}(T_k^{max}) \tag{3.4}$$

Second, we construct a leave-one-out weighted average of country-specific producer prices (reported by the FAO), weighting by harvested areas measured by Earthstat. The shock measure in Equation 3.4 isolates supply shortages from extreme heat, while the direct measurement of price captures all (potentially endogenous) shifts in international prices.

The two approaches described above take a comprehensive, global view of supply shortages. A methodological downside is that both measures vary only at the crop-year level. We must therefore exclude crop-year fixed effects and rely instead on the identification assumption that cross-country fluctuations in extreme heat exposure are as good as random. Another concern is that it seems unlikely that all foreign changes in extreme heat exposure are of equal relevance to policymakers. Countries may instead be more exposed to shocks that their trade partners experience.

Our third approach therefore measures markets' heterogeneous exposure to foreign extreme heat shocks. Using crop-level import and export data from the decade preceding our analysis, we compute exposures through import and export networks:

$$\text{ForeignExtremeHeat}^{M}_{\ell kt} = \sum_{\ell' \neq \ell} \text{ImportShare}_{\ell' \ell k} \cdot \text{ExtremeHeat}_{\ell' kt} \tag{3.5}$$

$$\text{ForeignExtremeHeat}^{X}_{\ell kt} = \sum_{\ell' \neq \ell} \text{ExportShare}_{\ell' \ell k} \cdot \text{ExtremeHeat}_{\ell' kt} \tag{3.6}$$

where $\text{ImportShare}_{\ell' \ell k}$ is the share of imports of crop k to ℓ that are from ℓ', and $\text{ExportShare}_{\ell' \ell k}$ is the share of exports of crop k to ℓ' that are from ℓ. Each measure captures the fact that adverse shocks might affect certain foreign countries more than others, even for a given crop in a given year. We then estimate an augmented version of Equation 3.1 that includes both local and foreign extreme heat shocks.

$$\text{NRA}_{\ell kt} = g(\text{ExtremeHeat}_{\ell kt}) + h(\text{ForeignExtremeHeat}_{\ell kt}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \varepsilon_{\ell kt} \tag{3.7}$$

Functions g and h are spanned by quartile indicators. When we define foreign extreme heat using Equation 3.4, we remove δ_{kt} from the regression. When we use the trade-weighted versions of foreign extreme heat, we assign export-weighted extreme heat shocks to net-exporting markets and import-weighted shocks to net-importing markets.[9]

[9]Table A.5 reports estimates using only the import- or export-weighted version of the shocks. It verifies that import-weighted shocks disproportionately affect NRA in net-importing markets and that export-weighted shocks disproportionately affect NRA in net-exporting markets.

Results. In Panel A of Table 2, we report estimates of Equation 3.7 using the foreign exposure measure of Equation 3.4. While we continue to find a negative effect of adverse domestic shocks on NRA, we find the *opposite* effect for foreign shocks. Higher foreign extreme heat exposure is associated with an increase in NRA, which indicates more producer-friendly policy. That is, food shortages induce the opposite policy responses when they arise from foreign shocks, rather than domestic shocks. Taking the coefficient estimates at face value, a top-quartile foreign temperature shock leads to an 18.5% policy-induced *increase* in domestic prices relative to international prices (column 1). Consistent with our baseline findings, these changes are driven by output-market policies (column 2) rather than input-market policies (column 3). The estimates are similar and larger in magnitude if we focus on the "major crops" of our baseline analysis (columns 4-6).

Consistent with these findings, Table A.6 shows that NRA responds positively to the international price (column 1), conditional on domestic shocks. However, the endogeneity of international prices may bias our estimates. We show that foreign extreme heat exposure acts as a supply shifter and places upward pressure on international prices (column 2). Instrumenting for international prices with foreign extreme heat, we estimate a larger and more precise positive response of NRA to international prices (column 3).

In Panel B of Table 2, we study the effect of shocks to trading partners, and we include crop-year fixed effects. We again find positive responses of NRA to foreign shocks (column 1) that are driven by output-market policies (columns 2-3) and that are larger for major crops (columns 4-6). These results imply that cross-market trade linkages are an important mechanism that ties foreign shocks to domestic policy responses.

Together, these results convey that domestic and foreign shocks induce opposite policy responses.[10] Our results are inconsistent with the "contagion of food restrictions" view of global policy, which instead suggests that domestic and foreign shocks lead to the same policy responses. Our results are also inconsistent with a view of the world in which all food security concerns induce the same policy response, with the sole objective of protecting consumers when food is scarce. In Section 4, we present a theoretical model that rationalizes these findings and draws a contrast with other models of policy conduct.

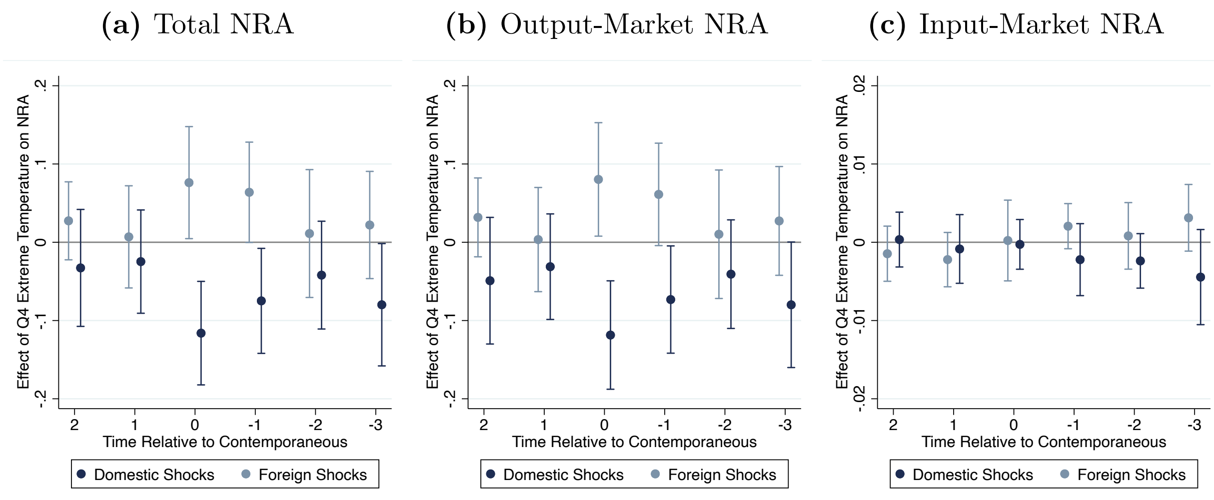
[10] One potential concern is that domestic and foreign extreme heat shocks may affect different markets. If so, differential responses may capture differences across markets rather than differences between domestic and foreign shocks. However, domestic and foreign shocks are *positively* correlated in our sample, with many markets exposed to both (Figure A.5). Moreover, the effect of foreign shocks does not seem to differ for countries that are more exposed to domestic shocks (Table A.4).

Table 2: Domestic versus Foreign Extreme Heat

	(1) NRA Overall	(2) NRA Output	(3) NRA Input	(4) NRA Overall	(5) NRA Output	(6) NRA Input
	All Crops			Major Crops		
Panel A: Aggregate Global Shocks						
Q2 Extreme Heat (Domestic)	-0.050	-0.049	-0.001	-0.060	-0.059	-0.002
	(0.024)	(0.024)	(0.001)	(0.033)	(0.033)	(0.001)
Q3 Extreme Heat (Domestic)	-0.055	-0.054	-0.001	-0.082	-0.077	-0.004
	(0.034)	(0.034)	(0.001)	(0.047)	(0.047)	(0.002)
Q4 Extreme Heat (Domestic)	-0.092	-0.094	-0.001	-0.264	-0.258	-0.004
	(0.052)	(0.053)	(0.002)	(0.110)	(0.110)	(0.003)
Q2 Extreme Heat (Foreign)	0.073	0.075	0.000	0.011	0.014	-0.001
	(0.050)	(0.050)	(0.001)	(0.046)	(0.047)	(0.001)
Q3 Extreme Heat (Foreign)	0.121	0.127	-0.000	0.120	0.150	-0.020
	(0.055)	(0.055)	(0.002)	(0.069)	(0.082)	(0.018)
Q4 Extreme Heat (Foreign)	0.185	0.188	0.002	0.221	0.244	-0.016
	(0.069)	(0.069)	(0.003)	(0.099)	(0.108)	(0.018)
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Crop-Year FE	No	No	No	No	No	No
Country-Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.714	0.712	0.808	0.734	0.735	0.766
Observations	15191	15191	15191	6838	6838	6838
Panel B: Trade-Weighted Shocks						
Q2 Extreme Heat (Domestic)	-0.029	-0.029	-0.001	-0.068	-0.068	-0.001
	(0.021)	(0.021)	(0.001)	(0.033)	(0.033)	(0.001)
Q3 Extreme Heat (Domestic)	-0.044	-0.043	-0.000	-0.087	-0.084	-0.003
	(0.026)	(0.026)	(0.001)	(0.042)	(0.042)	(0.002)
Q4 Extreme Heat (Domestic)	-0.136	-0.138	-0.001	-0.249	-0.244	-0.003
	(0.056)	(0.057)	(0.002)	(0.112)	(0.112)	(0.004)
Q2 Extreme Heat (Foreign)	0.031	0.032	-0.001	0.047	0.048	-0.001
	(0.020)	(0.021)	(0.001)	(0.030)	(0.031)	(0.002)
Q3 Extreme Heat (Foreign)	0.060	0.059	-0.003	0.070	0.070	-0.001
	(0.027)	(0.027)	(0.001)	(0.040)	(0.041)	(0.002)
Q4 Extreme Heat (Foreign)	0.084	0.086	-0.001	0.126	0.128	-0.001
	(0.031)	(0.032)	(0.002)	(0.059)	(0.059)	(0.005)
All Two-Way FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.832	0.830	0.786	0.798	0.798	0.769
Observations	11390	11390	11390	5887	5887	5887

This table reports the relationship between the nominal rate of assistance (NRA) and extreme heat in both domestic and foreign markets. The model is Equation 3.7, with g and h both parametrized by indicators for quartiles (with the first quartile of each as the excluded categories). The unit of observation in all specifications is a country-crop-year. In Panel A, foreign extreme heat is constricted as (leave one out) global area-weighted extreme heat exposure, and in Panel B, extreme heat exposure in each foreign market is weighted by either imports to or exports from the focal market. We apply export-weighted shocks to markets that were net exporters during the sample period and import-weighted shocks to markets that were net importers during the sample period. Across columns, we vary the outcome variable and the set of crops considered in the sample. Standard errors are clustered by market.

Figure 6: Dynamic Effects of Extreme Heat on Agricultural Policy



These figures report the dynamic relationship of the nominal rate of assistance (NRA) with both domestic and foreign extreme heat exposure. The model is Equation 3.8, with g and h parametrized by indicators for quartiles and the first quartile (at each lag) as the excluded category. The unit of observation is a country-crop-year and each. For concision, we report estimates only of the lead-and-lag coefficients on the fourth quartile of domestic and foreign extreme heat. The outcome variables are total NRA (Panel A), output-market NRA (Panel B), and input-market NRA (Panel C). Standard errors are clustered by market and error bars are 90% confidence intervals.

3.4 Policy Responses are Persistent

Our analysis focuses on how contemporaneous extreme heat shocks affect policy. But policy may respond to anticipated shocks, and shocks may have persistent effects on policy. We therefore re-estimate Equation 3.7 with leading and lagged shocks:

$$\text{NRA}_{\ell kt} = \sum_{s=-2}^{3} g(\text{EH}_{\ell k,t+s}) + \sum_{s=-2}^{3} h(\text{FEH}_{\ell k,t+s}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \varepsilon_{\ell kt} \tag{3.8}$$

where $\text{EH}_{\ell k,t+s}$ and $\text{FEH}_{\ell k,t+s}$ are domestic and foreign extreme heat exposure in year $t+s$. We use the trade-weighted version of foreign extreme heat so that all two-way fixed effects can be included in the regression, along with leads and lags of shock quartiles.

Figure 6 presents our estimates. The main outcome is average NRA (Panel A). For brevity, we only report the coefficient estimates on top-quartile exposure for domestic and foreign extreme heat. All coefficients on leading values are close to zero and statistically insignificant, implying no anticipation or pre-existing trends. The coefficients on lagged values indicate persistent policy effects. The effect of foreign extreme heat remains positive for one additional year, then reverts to zero two years after the shock. The effect of domestic extreme heat remains negative and significant, albeit smaller in magnitude, three years after the shock. Consistent with our previous findings, the policy response is driven by output-market policy (Panel B) and not input-market policy (Panel C).

To this point, our analysis has focused on how yearly fluctuations in extreme heat exposure affect yearly changes in policy. This annual variation is useful because it makes it possible to identify the effect of quasi-random variation in extreme heat exposure on policy. But the changes in policy due to climate change might be better approximated by the effects of longer-run changes in weather patterns (see, e.g., Burke and Emerick, 2016). While policy might respond to weather fluctuations in the short run, adaptation through production or trade might influence how policy responds to climate change over the long run. Moreover, the persistent effects documented in Figure 6 suggest that policy changes may accumulate over time, leading to larger policy effects over longer time horizons.

We investigate these possibilities by collapsing the data to the decade level and estimating versions of Equation 3.1 in which the unit of observation is a country-crop-decade triplet. Our independent variables of interest are (1) the number of years in a decade with high, fourth-quartile *local* exposure to extreme heat and (2) the number of years in a decade with high *foreign* exposure. Table 3 shows that higher decade-level exposure to domestic shocks reduces NRA, while exposure to foreign shocks has the opposite effect (column 1). The estimates are again larger in magnitude for economically important crops (column 2) and driven by output-market rather than input-market policy changes (columns 3-4). These estimates are larger than our annual estimates (Table 2), consistent with the persistence in policy responses documented in Figure 6. Column 2 suggests that each additional year of domestic extreme heat exposure reduces the decade's average NRA by 0.055. Ten years of extreme heat exposure, which occurs in 10% of the sample, reduce the decade's average NRA by 0.8 standard deviations and induces a 55% pro-consumer wedge in domestic prices relative to international prices. Thus, long-run shifts in the climate lead to large, long-run changes in global agricultural policy.

3.5 Mechanisms and Heterogeneity

Our baseline estimates capture the average effect of extreme heat shocks on food policy. But these estimates could mask substantial heterogeneity in government responses. We test for heterogeneity on a number of political and economic dimensions and, in doing so, highlight several important mechanisms linking temperature shocks to policy changes,

Table 3: Extreme Heat and Agricultural Policy at the Decadal Frequency

	(1) NRA Overall	(2) NRA Overall	(3) NRA Output	(4) NRA Input
	Full Sample	Major Crops		
Panel A: Aggregate Global Shock				
Q4 Extreme Heat (Domestic)	-0.032	-0.055	-0.053	-0.004
	(0.020)	(0.032)	(0.032)	(0.002)
Q4 Extreme Heat (Foreign)	0.021	0.027	0.028	0.001
	(0.011)	(0.012)	(0.012)	(0.001)
Country-Decade Fixed Effects	Yes	Yes	Yes	Yes
Crop-Decade Fixed Effects	No	No	No	No
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.707	0.760	0.762	0.744
Observations	2013	914	914	914
Panel B: Trade-Weighted Shocks				
Q4 Extreme Heat (Domestic)	-0.028	-0.063	-0.061	-0.004
	(0.014)	(0.035)	(0.035)	(0.002)
Q4 Extreme Heat (Foreign)	0.012	0.029	0.029	0.001
	(0.010)	(0.017)	(0.017)	(0.001)
Country-Decade Fixed Effects	Yes	Yes	Yes	Yes
Crop-Decade Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.803	0.780	0.781	0.738
Observations	1951	913	913	913

This table reports the relationship between extreme heat and the nominal rate of assistance at the decadal frequency. The unit of observation is the country-crop-decade and the independent variables are the number of fourth-quartile domestic or foreign extreme heat shocks that took place during the decade. In Panel A, we use shocks constructed using global (leave one out) area-weighted extreme heat, and in Panel B we use the trade-weighted version. In Panel B, all two-way fixed effects are included while in Panel A, crop-decade fixed effects are excluded. Standard errors are clustered by market.

while ruling out others.

Political Incentives. We first study the role of dynamic political incentives. A large literature on political cycles has documented that upcoming elections reduce fiscal responsibility and lead to policies designed to win the support of constituents (e.g. Alesina and Roubini, 1992; Akhmedov and Zhuravskaya, 2004; Balboni et al., 2021). If political incentives drive policy responses to extreme heat shocks, then we might expect upcoming elections to strengthen our estimates. To this end, we estimate an augmented version of Equation 3.1 that includes interaction terms between extreme heat exposure and (1)

Table 4: Policy Effects of Extreme Heat by Election Year

	(1)	(2)	(3)	(4)
	Dependent variable is NRA			
	All Crops	Major	Staple	Cash
Q2 Extreme Heat x No Election	-0.043	-0.072	-0.051	-0.026
	(0.025)	(0.042)	(0.051)	(0.061)
Q3 Extreme Heat x No Election	-0.014	-0.079	-0.056	-0.018
	(0.026)	(0.066)	(0.075)	(0.022)
Q4 Extreme Heat x No Election	-0.017	-0.095	-0.104	-0.013
	(0.037)	(0.096)	(0.102)	(0.025)
Q2 Extreme Heat x Election	-0.012	-0.069	-0.082	0.068
	(0.020)	(0.033)	(0.039)	(0.089)
Q3 Extreme Heat x Election	-0.036	-0.110	-0.145	0.022
	(0.025)	(0.052)	(0.062)	(0.022)
Q4 Extreme Heat x Election	-0.108	-0.382	-0.436	0.020
	(0.047)	(0.131)	(0.146)	(0.037)
p-value, Q4 x Election - Q4 x No Election	0.08	0.03	0.04	0.34
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop-Election Year Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.800	0.766	0.786	0.848
Observations	15860	7432	5671	2343

This table reports the relationship between extreme heat and the nominal rate of assistance (NRA) during election and non-election years. The unit of observation is a country-crop-year. The model is a variant of Equation 3.1 in which the variables that span g (quartiles of Extreme Exposure, with the first quartile omitted) are interacted with *Election*, an indicator that equals one in the year before or year during an election, and its complement *No Election.* The variables *Election* and *No Election* vary at the country-by-time level and are therefore absorbed in the corresponding fixed effect. The outcome variable and sample used in each specification are noted at the top of each column. Below each set of coefficients, we also report the p-value of the difference between a fourth-quartile shock during a non-election year and a fourth-quartile shock during an election year. Standard errors are clustered by market.

indicators for election years and (2) indicators for non-election years.[11]

We find substantially larger effects in the lead-up to elections (Table 4, column 1). Consistent with our main results, election effects are strongest for major and staple crops (columns 2-3) and muted for cash crops (column 4). In column 2, the effect of a top-quartile extreme heat shock is four times as large during an election year. Table A.7 shows that elections also intensify policy responses to foreign shocks. Electoral incentives and constituent demands serve to intensify intervention after extreme heat shocks.

[11]We define election years as the year during or immediately prior to any election. The results are qualitatively similar if we only include the election year itself.

We also study the role of political systems. We compile cross-country data on regime characteristics from the Polity IV project, which places countries on an index ranging from -10 (most autocratic) to 10 (most democratic). One hypothesis that would be consistent with our election results, as well as our motivating example of India, is that the incentives for responsive policies are stronger in democratic states, where constituents can express their displeasure with high food prices at the ballot box. We test this hypothesis with an empirical specification that is analogous to our elections specification, but with the Polity IV index as the interaction variable.

We find no statistically significant evidence of heterogeneity along this margin (Table 5, column 1). Our interpretation is that governments across the political spectrum face strong political incentives to limit food price increases, albeit for potentially different reasons. In democratic systems, unmitigated spikes in food prices may hurt the performance of democratic incumbents (e.g., Palmer and Whitten, 1999). In non-democratic systems, they might spur protest and other forms of opposition (e.g., during the Arab Spring; see Soffiantini, 2020). Marktanner et al. (2019) find that food price spikes harm incumbents in both democracies and autocracies, but the effect is *larger* in autocracies, where these shocks increase the likelihood of revolt.

Fiscal Incentives. At the same time, policy intervention incurs financial costs, and so policy responses may be more difficult for fiscally constrained governments. We proxy for fiscal constraints with countries' debt-to-GDP ratios, and we investigate whether this channel mediates policy responses to extreme heat shocks. We again estimate an interacted regression specification. We find that the negative effect of extreme heat exposure is substantially diminished when central government debt is high (Table A.8). The estimates are similar when we control flexibly for central government debt interacted with country-crop fixed effects (column 3) and when we control for extreme heat exposure interacted with the change in government debt, which captures year-to-year variation in fiscal policy and incumbent political orientation (column 4). Our model in Section 4 will formalize how fiscal and political incentives each shape governments' policy responses.

Economic Development. Broad differences in economic development and specialization may also shape policy responses to extreme heat shocks. For example, low-income countries may respond more forcefully to prevent domestic price increases if a larger share of the population faces potential food insecurity. However, we find no evidence of heterogeneity based on country income, as proxied by logged per capita GDP (Table 5, column

Table 5: Heterogeneous Effects of Extreme Heat on Agricultural Policy

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable is NRA					
Country-level characteristic ($Z_{\ell t}$)	Polity	GDP	GDP PC	Ag. Share	Urban Share	Import Share
Q2 Extreme Heat x $Z_{\ell t}$	-0.022	-0.047	-0.027	0.073	-0.031	0.018
	(0.035)	(0.045)	(0.029)	(0.039)	(0.030)	(0.028)
Q3 Extreme Heat x $Z_{\ell t}$	0.022	-0.033	-0.049	0.104	-0.061	0.001
	(0.059)	(0.068)	(0.050)	(0.060)	(0.048)	(0.049)
Q4 Extreme Heat x $Z_{\ell t}$	0.045	0.077	-0.023	0.183	-0.239	-0.738
	(0.100)	(0.142)	(0.100)	(0.092)	(0.100)	(0.286)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Z-Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.775	0.778	0.776	0.786	0.777	0.774
Observations	7439	7439	7439	6508	7435	7318

This table reports the relationship between the nominal rate of assistance (NRA) and extreme heat, interacted with country-level characteristics. The model is a variant of Equation 3.1 in which the variables that span g (quartiles of Extreme Exposure, with the first quartile omitted) are interacted with the indicated country-level characteristics $Z_{\ell t}$. The unit of observation is a country-crop-year. For concision, we report only the coefficients on the interaction coefficients. The characteristics $Z_{\ell t}$, all converted to standardized units, are the Polity score from the Polity IV project (column 1; higher values correspond to more democratic regimes); log GDP (column 2), log per-capita GDP (columns 3), agriculture's share of GDP (column 4) and the urban population share (column 5), all measured from the World Bank; and the share of food consumption that is imported, constructed as the value of imports normalized by the value of production plus imports minus exports. The direct effects of these characteristics are absorbed in the country-by-time fixed effect. Standard errors are clustered by market.

2), or based on country size, as proxied by logged total GDP (Table 5, column 3). These estimates again suggest that most governments have an incentive to prevent domestic supply shortages from raising domestic prices.

We next investigate whether policy responses are mediated by interest groups within countries. First, we find somewhat muted policy responses in countries with larger agricultural sectors, as proxied by the agricultural share of GDP (Table 5, column 4). Even so, the coefficient estimates suggest that the effect of extreme heat shocks on NRA remains negative for roughly 95% of the sample, suggesting that this force is rarely sufficient to flip the sign of the baseline policy response. Second, we find larger policy responses in countries with a higher urban population share (Table 5, column 5), indicating that governments are perhaps especially responsive to the demands of urban constituents. Indeed, prior work suggests that urban residents can most effectively lobby and threaten the legitimacy of incumbents (Bates, 2014). Third, we find larger policy responses in countries that are more dependent on foreign nations for food consumption (Table 5, column 6), highlighting the importance of food security concerns more broadly.

Finally, we use the Household Impact of Tariffs (HIT) database to investigate whether policy responses are mediated by their potential distributional consequences across domestic income groups. For a large set of products and countries, we observe how much each product in each country contributes to the consumption and expenditure of residents in each income centile. For each country, we link HIT products to crops in our data, and we compute the share of expenditure on each crop for (1) the top income quartile, (2) the top two income quartiles, (3) the bottom two income quartiles, and (4) the bottom income quartile. We also compute the share of income generated by each crop for each of these four groups. While our estimates are imprecise because of the smaller sample covered by HIT, policy seems to be more responsive to crops consumed disproportionately by lower-income constituents and less responsive to crops produced disproportionately by lower-income constituents (Table A.9, Panels A and B). Governments are perhaps especially responsive to the subsistence demands of the most needy.

4 Why Does Food Policy React to Shocks?

We next show that our full set of empirical results can be rationalized with a model of trade policy as an instrument for domestic redistribution. We also discuss why alternative models predicated on insurance motives and price stabilization are less consistent with our empirical results.

4.1 A Model of Food Policy and Redistribution

We model the market for a single agricultural commodity from the perspective of a home country. Consumers' inverse demand is $q = D(p) = p^{-\varepsilon_d}$, where $\varepsilon_d > 0$ is the elasticity of demand. Producers' supply curve is $y = Y(p, \omega) = \omega p^{\varepsilon_s}$, where $\varepsilon_s > 0$ is the elasticity of supply and ω is a productivity shock that increases domestic production. International markets are summarized by net demand ("exports") curve $x = X(p, \omega') = \omega' p^{-\varepsilon_x}$, where $\varepsilon_x > 0$ is the elasticity of export demand and ω' is a shock that increases export demand. We assume that $\varepsilon_d < \varepsilon_x < \infty$ and $\varepsilon_x > 1$, such that foreign demand is sufficiently price elastic, but not infinitely so. In Appendix A, we show that all results extend to the case of a net importer facing isoelastic foreign net supply.

The government can impose an *ad valorem* border tax $\alpha > -1$ that places a wedge between domestic and international prices. That is, $p^* = (1 + \alpha)p^I$, where p^* is the domestic equilibrium price and p^I is the international price. Positive α corresponds to an export subsidy, and negative α to an export tax. Government expenditures are therefore $\alpha p^I = \frac{\alpha}{1+\alpha}p^*$ per exported unit. The market clears at a domestic equilibrium price p^* such that $Y(p^*, \omega) = Q(p^*) + X\left(\frac{p^*}{1+\alpha}, \omega'\right)$. In the model, border tax α exactly corresponds to the definition of the nominal rate of assistance (Section 2.1). We focus on a border tax as the sole policy instrument because governments primarily use trade policy to respond to extreme heat shocks (Section 3.2).

The government chooses a tax α^* to maximize a weighted sum of consumer surplus, producer surplus, and government revenue:

$$\begin{aligned} \alpha^* \in \underset{\alpha\in[-1,\infty)}{\arg\max} & \left\{ \lambda^C \int_{p^*}^{\bar{p}} Q(p)\,\mathrm{d}p + \lambda^P \int_0^{p^*} Y(p,\omega)\,\mathrm{d}p - \lambda^G \frac{\alpha}{1+\alpha} p^* X\left(\frac{p^*}{1+\alpha}, \omega'\right) \right\} \\ \text{s.t. } & p^* = P^*(\alpha, \omega, \omega') \end{aligned} \tag{4.1}$$

where $\lambda^C, \lambda^P, \lambda^G > 0$ are parameters, $\bar{p}$ is an (arbitrarily large) maximum price, and P^* describes the mapping from policy and shocks to the equilibrium price.[12]

Micro-foundation. We provide an explicit link to a micro-founded production economy. Consider heterogeneous households indexed by $i \in \{1, \dots, N\}$ and two goods, the agricultural good and "money" as numeraire. Each household consumes both goods and produces the agricultural good with some resource cost. Their payoff in terms of agricultural consumption q_i, money consumption z_i, and production y_i is

$$\mathcal{U}_i = \mu_i^{\frac{1}{\varepsilon_d}} \frac{q_i^{1-\frac{1}{\varepsilon_d}}}{1-\frac{1}{\varepsilon_d}} - (\omega\psi_i)^{-\frac{1}{\varepsilon_s}} \frac{y_i^{1+\frac{1}{\varepsilon_s}}}{1+\frac{1}{\varepsilon_s}} + z_i, \tag{4.2}$$

where household heterogeneity is captured in tastes for the agricultural good μ_i and agricultural productivity ψ_i. As a normalization, we set $\sum_{i=1}^N \mu_i = \sum_{i=1}^N \psi_i = 1$. Each household has the budget constraint, $pq_i + z_i \leq py_i + T_i$, where p is the price of the agricultural good and T_i is a government transfer. Transfers are determined by the rule $T_i = \xi_i \mathcal{G}$, where the ξ_i are positive weights such that $\sum_{i=1}^N \xi_i = 1$ and $\mathcal{G}$ is total tax revenue. Trade, market clearing, and the government policy instrument are as described

[12] We assume that primitives are such that this problem is quasi-concave in α. The finite limit of integration $\bar{p}$ allows us to study preferences that generate non-integrable demand curves (i.e., $\varepsilon_d \leq 1$).

above. The government's objective is to maximize a social welfare function $\mathcal{W} = \sum_{i=1}^{N} \lambda_i \mathcal{U}_i$ with Pareto weights $\lambda_i \in [0, 1]$ and normalization $\sum_i^N \lambda_i = 1$. These micro-foundations map to our original model as follows.

Lemma 1. *The competitive equilibrium in this economy coincides with the "supply and demand" representation described above. The government's preferences coincide with those in Equation 4.1:*

$$\lambda^C = \sum_{i=1}^{N} \mu_i \lambda_i, \quad \lambda^P = \sum_{i=1}^{N} \psi_i \lambda_i, \quad \lambda^G = \sum_{i=1}^{N} \xi_i \lambda_i \tag{4.3}$$

where μ_i is household i's share of domestic consumption and ψ_i is household i's share of domestic production. If $\lambda_i = 1/N$ for all i, then $\lambda^C = \lambda^P = \lambda^G$.

Proof. See Appendix A.1. □

The parameters $(\lambda^C, \lambda^P, \lambda^G)$ are weighted averages of the government's primitive weights over individuals. The government has a high λ^C if its preferred agents consume more of the good and are therefore more exposed to changes in its price. The same holds for λ^P and production. The government has a high λ^G if its existing transfer schemes already effectively target its preferred agents.

This framework nests a range of potential political preferences and/or institutions, which map to different aggregate weights $(\lambda^C, \lambda^P, \lambda^G)$. As one example, consider a progressive government that places higher weights λ_i on poorer households. If the poor disproportionately consume a good, as is likely for staple crops, then λ^C is high. If the poor disproportionately produce a good, as is likely for smallholder-driven production, then λ^P is high. If government transfer policies are particularly effective at reaching the poor, then λ^G is high. As a second example, consider a government that seeks to redistribute resources away from from participants in agricultural markets to target other interest groups, such as corrupt officials or their own patronage network. In this case, aggregate λ^G would be high relative to λ^C and λ^P. If, on the other hand, government transfers are a "leaky bucket" (Okun, 1975) and are unlikely to reach the intended recipient, the opposite would be true. More generally, if countries have different weighting schemes across individuals for any reason, aggregate weights $(\lambda^C, \lambda^P, \lambda^G)$ will also differ.

4.2 Optimal Policy and its Response to Shocks

Optimal Policy. We describe optimal policy in terms of the primitive elasticities, the government's welfare weights, and an equilibrium sufficient statistic, the *self-sufficiency ratio* $r = \frac{y}{q}$.

Proposition 1. *The optimal policy satisfies*

$$\alpha^* = \frac{1}{\varepsilon_x}\left(\frac{\varepsilon_x\left(\lambda^P r + \lambda^G(1-r) - \lambda^C\right) - \lambda^G\left(\varepsilon_s r + \varepsilon_d\right)}{\lambda^G\left(\varepsilon_s r + \varepsilon_d\right) - \left(\lambda^P r + \lambda^G(1-r) - \lambda^C\right)}\right). \tag{4.4}$$

Moreover, α^* increases in λ^P and decreases in λ^C.

Proof. See Appendix A.2 □

Under the utilitarian case ($\lambda^P = \lambda^C = \lambda^G$), optimal policy reduces to $\alpha^* = -1/\varepsilon_x$. This "inverse elasticity rule" sets marginal revenue equal to marginal deadweight loss: exporting countries set export taxes (and importing countries set import taxes) proportional to their ability to manipulate terms-of-trade. Policy would *not* respond to shocks.

More generally, policy depends on governments' desire to use agricultural policy as a tool for redistributing across groups. These policies vary widely. Anecdotally, large agricultural producers in the United States and European Union exert influence that leads to large production subsidies, while urban consumers in lower-income countries hold political sway that leads to large consumer subsidies (Bates, 2014). These observations are corroborated by cross-sectional patterns in our own data (Figure A.4). Our model accommodates these distributional motives: high λ^P favors producers, motivating high α that elevates domestic prices above world prices, while high λ^C favors consumers.

How Policy Responds to Shocks. We study how trade policy responds to shocks. We first define a key condition on preferences and the elasticities of supply and demand.

Definition 1. *The government is redistribution-focused in a given agricultural market if*

$$\frac{\varepsilon_s\lambda^C + \varepsilon_d\lambda^P}{\varepsilon_s + \varepsilon_d} > \lambda^G. \tag{4.5}$$

The government is revenue-focused if the opposite inequality holds.

The government is *redistribution-focused* if it places relatively high weight on consumers *or* producers and relatively low weight on revenue. Our micro-foundation of government preferences (Lemma 1) suggests a natural interpretation: that the government is greatly concerned with the redistribution between consumers and producers that occurs when prices change. The government is *revenue-focused* if it places relatively high weight on the fiscal cost of policy intervention. A utilitarian government is exactly between redistribution and revenue focus, such that Equation 4.5 holds at equality. These distinctions determine how trade policy responds to shocks.

Proposition 2. *Optimal policy responds to shocks as follows.*

1. *If the government is redistribution-focused, then α^* increases in ω and ω'.*
2. *If the government is revenue-focused, then α^* decreases in ω and ω'.*

Proof. See Appendix A.3. □

The redistribution-focused case of the model generates predictions that are consistent with our empirical evidence. In response to domestic extreme heat shocks, which decrease domestic supply, governments reduce the nominal rate of assistance and lower the price of food (Section 3.1). In response to foreign extreme heat shocks, which increase foreign net demand (or equivalently, decrease foreign net supply), governments increase the nominal rate of assistance and raise the price of food (Section 3.3). The revenue-focused case of the model makes the opposite predictions.

Intuition for the Result. Shocks affect government incentives through two channels, which push in opposite directions. We give the intuition for both channels in the case of a domestic supply shock that lowers production.

First, shocks shift the incidence of prices between domestic and foreign consumers and producers (the "redistribution channel"). The government places positive weight on its own constituents, but zero weight on foreign producers and consumers. Regardless of whether the government cares more about domestic producers *or* consumers, this channel pushes toward more pro-consumer policy following a domestic adverse supply shock. A pro-*consumer* government initially taxes exports to assist consumers by lowering domestic prices. This policy cross-subsidizes foreign producers by raising world prices. An adverse domestic supply shock reduces exports, lowering the cross-subsidy to foreign producers and allowing the government to better target domestic consumers. The government responds by raising the export tax, thereby lowering domestic prices and helping consumers. A pro-*producer* government initially subsidizes exports to assist producers by raising domestic prices. An adverse domestic shock reduces production, lowering the marginal returns to producer price support. The government responds by reducing the export subsidy, again lowering domestic prices and helping consumers. Thus, the redistribution channel pushes policy in a more pro-consumer direction following adverse supply shocks, regardless of whether it places a higher weight on domestic consumers or producers.

Second, shocks affect how marginally profitable trade policy is for the government (the "revenue channel"). A domestic supply shortage is the least profitable time to marginally tax exports, or the least costly time to marginally subsidize exports, because the volume of exports is low. The government responds by reducing export taxes, or raising export subsidies, thereby raising domestic prices and helping producers. Thus, the revenue channel pushes in the opposite direction of the redistribution channel.[13] The strength of this channel depends on the weight that governments place on revenue generation, which in turn is higher when revenue is redistributed in a more socially valuable way.

Whether the government is redistribution-focused or revenue-focused (Equation 1) precisely determines which channel is stronger. Following an adverse domestic supply shock, a redistribution-focused government is more swayed by the marginal incentives to lower prices, whereas a revenue-focused government is more swayed by the marginal incentives to raise prices.

Domestic Versus Foreign Shocks. An important corollary is that domestic and foreign supply shocks induce opposite policy responses. A domestic supply shock is given by a low ω, which decreases domestic production. A foreign supply shock is given by a high ω', which increases exports by increasing foreign net demand. By proposition 2, these shocks induce opposite policy responses for both redistribution- and revenue-focused governments. The reason is that the self-sufficiency ratio r is a sufficient statistic for how shocks affect optimal policy (Equation 4.4). A domestic supply disruption reduces self-sufficiency, while a foreign supply disruption increases it. Opposite impacts on self-sufficiency imply opposite impacts on policy.

4.3 Rationalizing Our Empirical Results

Our model of trade policy and redistribution can rationalize our full set of empirical findings in Section 3. First, the model rationalizes government intervention to assist con-

[13]Both channels have a related intuition for an importing country. A pro-consumer importer subsidizes imports at baseline and does so more aggressively when these subsidies can better target domestic consumers; a pro-producer importer taxes imports at baseline but reduces these taxes when low production implies low returns to producer price support. Finally, a domestic supply shortage increases the marginal cost of subsidizing imports and the marginal benefit of taxing them.

sumers in response to domestic supply shortages, as we found in Section 3.1. While intervention during a domestic supply shortage is particularly costly, a redistribution-focused government prioritizes redistribution among consumers and producers. Second, the model formalizes why policy responses are similar across countries that otherwise differ in their trade balance and initial policies. In particular, countries can be redistribution-focused whether they are net importers or exporters and whether they are rich or poor, as we found in Sections 3.2 and 3.5. These determinants of *average* incentives are separate from the determinants of *marginal* incentives. Third, the model predicts that domestic and foreign supply shocks induce opposite policy responses, as we found in Section 3.3. The reason is that domestic and foreign shocks have opposite implications for domestic redistribution. Fourth, the model is consistent with the heterogeneity that we document across crop types, political incentives, and fiscal incentives. The model predicts stronger policy responses for staple crops (Figure 4) if these crops are essential for more constituents (Section 4.1). Moreover, elections and debt burdens strengthen governments' redistribution and revenue motives, respectively, consistent with our estimates from Tables 4 and A.8.

Our model of trade policy and redistribution extends related work from the literature on political economy and trade. These models include the canonical theory of Grossman and Helpman (1994), which can be understood as one in which government preferences are endogenously biased toward producers because of political lobbying. In this set of models, import penetration is a key determinant of policy (see also Goldberg and Maggi, 1999; Maggi and Rodríguez-Clare, 2000). In our application, extreme heat shocks to domestic and foreign supply directly affect import penetration, and thereby affect policy.

4.4 Alternative Models

Alternative models of agricultural policymaking may also predict that governments react to adverse production shocks. We highlight two such models that are surely relevant in practice, but explain why they cannot by themselves rationalize all of our empirical results.

Helping the Poor. Governments may aim to help poor households by maintaining low food prices. Poor households spend a larger share of their income on food, and they are more vulnerable to falling below subsistence levels when food prices rise. Concave utility implies that poor households suffer larger losses from high food prices more generally. This might be especially true for staple crops, which could rationalize our heterogeneous effects across crops. In this model, adverse production shocks—either domestic or foreign—

place upward pressure on domestic prices and, In response, governments tax exports (or subsidize imports) to maintain low domestic prices.[14] Thus, this motive encourages the same policy response to domestic and foreign shocks. However, we document opposite policy responses in the data. Moreover, we find no evidence that the results are stronger for poor countries, where a larger share of the population is close to subsistence.

Price Stabilization. Governments may independently aim to stabilize domestic food prices around a target level, effectively providing insurance against price volatility. Again, domestic and foreign shocks place the same upward pressure on domestic prices, and governments can respond by taxing exports (or subsidizing imports) to maintain low prices. Thus, this motive encourages the same policy response to domestic and foreign shocks. By contrast, we find opposite policy responses in the data. That is, governments *stabilize* price fluctuations in one case and *amplify* price fluctuations in another.

5 Counterfactuals

We finally combine our empirical estimates and model to quantify how agricultural policy responses shape the aggregate and distributional effects of extreme heat shocks.

5.1 Quantification

We describe a multi-crop, multi-country version of the model that we take to data and use for simulation. We keep the model intentionally simple on several margins to stay as close as possible to our empirical estimating equations. This quantitative model allows us to quantify welfare effects in equilibrium, characterize the incidence of damages, and isolate the role of policy responses.

Model. We specify isoelastic curves for demand $q_{\ell kt}$ and supply $y_{\ell kt}$.

$$\log q_{\ell kt} = \log q^0_{\ell kt} - \varepsilon_d \log p_{\ell kt}, \tag{5.1}$$

$$\log y_{\ell kt} = \log y^0_{\ell kt} + \varepsilon_s \log p_{\ell kt} + f(\text{ExtremeHeat}_{\ell kt}) \tag{5.2}$$

for countries ℓ, crops k, years t, quantities $(q_{\ell kt}, y_{\ell kt})$, prices $p_{\ell kt}$, domestic $\text{ExtremeHeat}_{\ell kt}$, intercepts $(q^0_{\ell kt}, y^0_{\ell kt})$, and elasticities $(\varepsilon_d, \varepsilon_s)$. Damage function f captures the effect of

[14] Formally, we can extend our micro-foundation as follows. Household utility is $\tilde{\mathcal{U}}_i = v(\mathcal{U}_i)$, where v is concave and differentiable. We adopt the first-order approximation $v(\mathcal{U}_i) \approx v'(\mathcal{U}_i)\mathcal{U}_i$ and say that the government maximizes social welfare $\tilde{\mathcal{W}} = \sum_{i=1}^N \lambda_i v'(\mathcal{U}_i)\mathcal{U}_i$, which aggregates household payoffs $\mathcal{U}_i$ with endogenous Pareto weights $\tilde{\lambda}_i = \lambda_i v'(\mathcal{U}_i)$. If food-price shocks disproportionately raise the marginal utility of poor consumers, then λ^C rises (Lemma 1) and α falls (Proposition 1).

domestic extreme heat exposure on production. Government policy $\alpha_{\ell kt}$ is given by

$$\alpha_{\ell kt} = \alpha^0_{\ell kt} + g(\text{ExtremeHeat}_{\ell kt}) + h(\text{ForeignExtremeHeat}_{\ell kt}), \tag{5.3}$$

where policy functions g and h capture the effects of domestic $\text{ExtremeHeat}_{\ell kt}$ and $\text{ForeignExtremeHeat}_{\ell kt}$ on policy. Policy takes the form of *ad valorem* tariffs $\alpha_{\ell kt}$ on international prices p^I_{kt}, such that domestic prices $p_{\ell kt} = (1 + \alpha_{\ell kt})p^I_{kt}$. Markets clear internationally for each crop in each year. That is, given exposure $\omega_{kt} = \{\text{ExtremeHeat}_{\ell kt}, \text{ForeignExtremeHeat}_{\ell kt}\}_\ell$ and policy $\alpha_{kt} = \{\alpha_{\ell kt}\}_\ell$ across countries ℓ, the vector of international prices $\{p^I_{kt}\}_{kt}$ solves

$$\sum_\ell q_{\ell kt}(p^I_{kt}; \omega_{kt}, \alpha_{kt}) = \sum_\ell y_{\ell kt}(p^I_{kt}; \omega_{kt}, \alpha_{kt}) \quad \forall\ k, t \tag{5.4}$$

Equilibrium world prices then give equilibrium domestic prices, quantities, trade flows, and welfare. Trade flows $\mathcal{T}$ include the value of imports and exports. Welfare $\mathcal{W}$ sums over consumer surplus $\mathcal{C}$, producer surplus $\mathcal{P}$, and government revenue $\mathcal{G}$ with equal weights. We take this welfare measure as a utilitarian benchmark, noting that governments may pursue other objective functions.[15] We aggregate as follows. We define expenditure shares $e_{\ell kt} = p_{\ell kt}q_{\ell kt}/E$ as a function of total consumption expenditures $E = \sum_{\ell kt} p_{\ell kt}q_{\ell kt}$. For domestic prices p, we compute Stone price indices that weight by these expenditure shares. For trade $\mathcal{T}$, we compute the sum and divide by two (to avoid double counting imports and exports). For welfare measures $W \in \{\mathcal{W}, \mathcal{C}, \mathcal{P}, \mathcal{G}\}$, we compute sums.

$$\ln p = \sum_{\ell kt} e_{\ell kt} \ln p_{\ell kt}, \quad \mathcal{T} = \frac{1}{2}\sum_{\ell kt} \mathcal{T}_{\ell kt}, \quad W = \sum_{\ell kt} W_{\ell kt} \tag{5.5}$$

Measurement. For each country, crop, and year, we observe consumption $q_{\ell kt}$, production $y_{\ell kt}$, NRA policy $\alpha_{\ell kt}$, world prices p^I_{kt}, $\text{ExtremeHeat}_{\ell kt}$, and $\text{ForeignExtremeHeat}_{\ell kt}$. Our study period is 1991 to 2019.[16] We further restrict attention to countries and crops for which we observe policy. We account for the rest of the world by computing the differences between observed production and consumption for each crop-year in our study

[15] We compute imports $\mathcal{M}_{\ell kt} = p_{\ell kt}(q_{\ell kt} - y_{\ell kt})^+$, exports $\mathcal{X}_{\ell kt} = p_{\ell kt}(y_{\ell kt} - q_{\ell kt})^+$, trade flows $\mathcal{T}_{\ell kt} = \mathcal{M}_{\ell kt} + \mathcal{X}_{\ell kt}$, consumer surplus $\mathcal{C}_{\ell kt} = \frac{q_{\ell kt}p_{\ell kt}}{\varepsilon_d - 1}$, producer surplus $\mathcal{P}_{\ell kt} = \frac{y_{\ell kt}p_{\ell kt}}{\varepsilon_s + 1}$, government revenue $\mathcal{G}_{\ell kt} = (p_{\ell kt} - p^I_{kt})(q_{\ell kt} - y_{\ell kt})$, and total welfare $\mathcal{W}_{\ell kt} = \mathcal{C}_{\ell kt} + \mathcal{P}_{\ell kt} + \mathcal{G}_{\ell kt}$.

[16] Our regression sample covers 1980 to 2011. For counterfactuals, we draw our price data from the FAO, which only maintains price data from 1991. We incorporate more recent data from the Ag-Incentive project, which extends the NRA series, to reach 2019.

sample, then holding these differences fixed in counterfactuals.

We calibrate demand elasticities ε_d with country-crop-specific estimates compiled by the USDA Commodity and Food Elasticities database, which draws on demand estimates from 77 studies covering 117 countries (USDA 2011).[17] The average estimate is $\bar{\varepsilon}_d = 0.4$. We set supply elasticities $\varepsilon_s = 1$ following Alston et al. (1995). We directly incorporate our prior regression estimates: Section 2.5 estimates damages f from extreme heat exposure, and Section 3 estimates policy responses g and h to domestic and foreign exposure. We recover intercepts $(q^0_{\ell kt}, y^0_{\ell kt}, \alpha^0_{\ell kt})$ as residuals to fit the observed data.

Extreme heat shocks are given by the difference between observed exposure and a hypothetical baseline of minimal exposure. We define baseline domestic exposure to be the lowest domestic exposure that we observe over time for each country-crop.

$$\text{BaselineHeat}_{\ell k} = \min_t \{\text{ExtremeHeat}_{\ell kt}\} \; \forall \, \ell, k \tag{5.6}$$

We then compute baseline foreign exposure with Equation 3.5. Table A.10 converts these baseline values into quartiles, as defined in our regression specifications, and tabulates them against observed exposure. Observed domestic exposure exceeds baseline domestic exposure by one quartile for 34% of country-crop-year markets. The same applies for foreign exposure for 30% of markets.

Damages. We evaluate damages from extreme heat shocks, and we characterize incidence across markets. We do so by comparing outcomes under observed exposure, as measured in the data, to outcomes under baseline exposure, as simulated with the model. We proceed in two steps.

First, we quantify impacts on production and policy. In particular, differences between observed and baseline values represent shock-induced production losses and policy responses. We compute production and policy under baseline exposure with Equations 5.2 and 5.3, directly applying our regression estimates of damage function f and policy functions g and h. The benefit of this approach is that it accommodates any model consistent with our regression estimates. The cost is that it constrains production and policy to respond only as we observe in the data. Our definition of baseline remains within the support of the data, thereby minimizing this cost.[18]

[17] The database includes 2,803 own-price elasticity estimates, which we assign to four crop groups: cereals, oils, fruits and vegetables, and other crops. We compute the average estimated elasticity for each country and crop group.

[18] Rather than using our empirical estimates $\hat{g}$ and $\hat{h}$, we could use observed policies to estimate the

Second, we quantify impacts on prices, quantities, trade, and welfare. We solve for these quantities in equilibrium. For each, we compute standard errors by applying the delta method and the variance-covariance matrix from our regression estimates. We obtain market-specific measures that allow us to study the incidence of damages, which vary richly across markets. Markets differ in their domestic shocks given variation in extreme heat exposure. Markets differ in their foreign shocks given variation in trade partnerships. And markets differ in their shock-induced policies given variation in baseline policies.

Decomposition. We isolate the role of policy reponses with a decomposition exercise. Consider outcome $x(\omega, \alpha)$ under exposure $\omega = \{\omega_{\ell kt}\}_{\ell kt}$ and policy $\alpha = \{\alpha_{\ell kt}\}_{\ell kt}$. We define a shock as a change from exposure ω to ω', and policy responses by the resulting change from policy α to α'. We compute shock-induced changes under responsive and unresponsive policy, which we decompose as follows.

$$\underbrace{x(\omega', \alpha') - x(\omega, \alpha)}_{\Delta x^R} = \underbrace{x(\omega, \alpha') - x(\omega, \alpha)}_{\Delta x^U} + \underbrace{x(\omega', \alpha') - x(\omega, \alpha')}_{\Delta x^R - \Delta x^U} \tag{5.7}$$

The change Δx^R under responsive policy is the total effect of the shock. The total effect includes two components. The first component is the change Δx^U under unresponsive policy. This *production effect* captures the direct impact of the shock on domestic production, holding policy fixed. The second component is the difference $\Delta x^R - \Delta x^U$ in changes under responsive and unresponsive policy. This *policy effect* isolates the indirect impact of the shock through the policy responses that it induces.

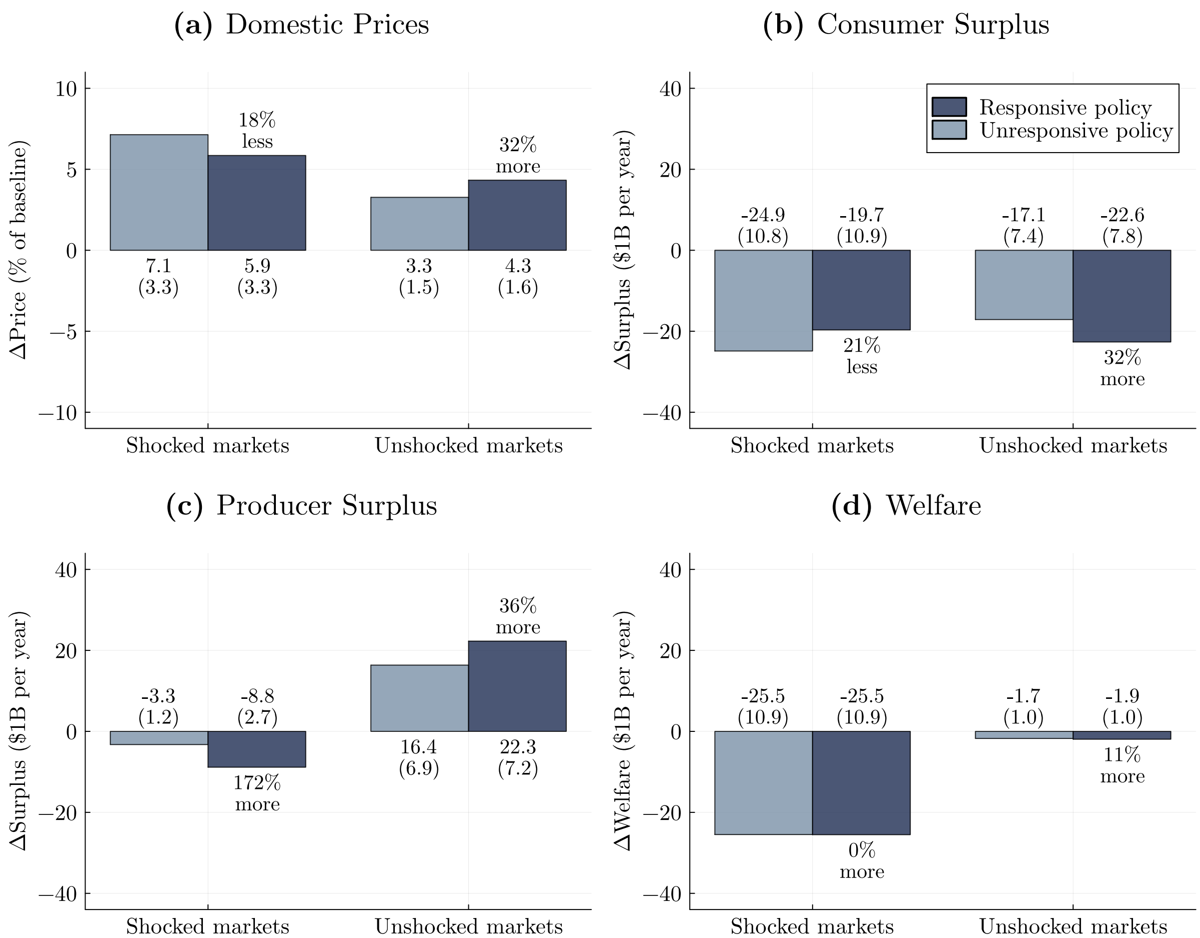
5.2 Results

Policy responses re-shape the economic impacts of extreme heat shocks. We first document how policy responses redistribute economic losses across producers and consumers, and across markets, by shifting market prices. We then document the aggregate welfare consequences of endogenous policy and its heterogeneous effects across countries. Finally, we investigate how policy responses might re-shape the consequences of the more extreme temperature change that is projected to take place as global warming progresses.

Redistribution. Policy responses redistribute welfare losses by affecting market prices. Figure 7a shows that policy responses stabilize prices in markets that experience extreme

structural parameters of governments' objective functions under a specific dynamic equilibrium concept for policymaking (e.g., Markov perfect equilibrium). This approach might better extrapolate beyond the data, but it would be tied to specific and difficult-to-test assumptions.

Figure 7: Redistribution through Market Prices



We compute shock-induced changes under responsive and unresponsive policy. Shocks are observed extreme heat shocks from 1991 to 2019. Responsive policy adjusts as estimated, and unresponsive policy is fixed at baseline levels. We aggregate over countries, crops, and years as follows. For domestic prices, we compute Stone price indices, which weight by expenditure shares, and we report percentage changes relative to baseline prices. For consumer surplus, producer surplus, and welfare, we compute sums and report changes in billions of dollars per year relative to baseline levels. Dollars are inflation-adjusted, year-2020 USD. We report effects separately for shocked markets, which experience domestic extreme heat shocks (34% of markets), and for unshocked markets, which do not (66% of markets). We report standard errors in parentheses.

heat shocks. Prices rise by 7.1% under unresponsive policy, compared to 5.9% under responsive policy, meaning that policy responses dampen price increases by 18% on average. Figure A.7 shows that policy responses tend to increase price volatility, as well as surplus volatility for most markets, and Figure A.8 accounts for policy response dynamics and finds cumulative price effects over three years to be roughly twice as large as immediate price effects. Both findings suggest that, if anything, the results from the remainder of section likely understate the effect of responsive policy on surplus changes.

These agricultural market interventions shift welfare losses from consumers to producers in heat-shocked markets. Consumer surplus losses fall by 21% across shocked markets, and consumers gain over $5B annually (Figure 7b). Producer surplus losses more than double, however, rising by 172% (Figure 7c). Without policy responses, producer losses are modest at $3.3B per year because relatively inelastic agricultural demand allows for large price spikes that hedge producers against production losses. Policy responses minimize price increases, leaving producers to bear the double burden of production losses and policy pressures. The result is an additional $5.5B per year in losses for producers.

Policy responses also affect markets that do not themselves experience extreme heat shocks. Unshocked markets face higher world prices, which rise in equilibrium as shocked markets respond to domestic shocks with pro-consumer policy. Unshocked markets also respond to foreign shocks with pro-producer policy, raising domestic prices further. Quantitatively, we find that policy responses amplify price increases in unshocked markets by 33%: extreme heat shocks increase prices by 3.3% under unresponsive policy, but by a larger 4.3% under responsive policy (Figure 7a). In turn, foreign consumers suffer 32% larger consumer surplus losses (Figure 7b), while foreign producers enjoy 36% larger producer surplus gains (Figure 7c). Even with unresponsive policy, unshocked producers gain as prices rise with reduced competition from shocked producers. With responsive policy, unshocked foreign producers gain even more as policy responses amplify the rise in prices.

If the world were one with free trade, then policy responses would decrease social welfare by introducing policy wedges and reducing efficient trade. But global agricultural markets have significant distortions, which policy responses can either magnify or diminish. Figure 1 shows large variation in NRA policy, which creates both positive and negative price wedges. The magnitude of these wedges in absolute value terms captures policy distortions. Table A.10 shows that policy responses magnify baseline distortions for 19% of markets and diminish baseline distortions for 35% of markets. In shocked markets, total welfare losses exceed $25B per year, but are similar under responsive and unresponsive policy (Figure 7d). Diminished distortions offset magnified distortions and lead to neutral welfare impacts on net. Welfare losses are smaller in unshocked markets, but again similar under responsive and unresponsive policy.[19]

[19]Table A.12 decomposes these welfare impacts by policy response. Responses to domestic shocks worsen utilitarian welfare losses in shocked markets and reduce losses in unshocked markets. Responses

Country-Level Impacts of Responsive Policy. Policy responses have vastly different impacts across countries. We compute country-level policy effects as differences between shock-induced changes under responsive and unresponsive policy and report these differences as percentages of shock-induced changes under unresponsive policy. The net effect of global policy responses is to improve utilitarian welfare in 38% of countries, while reducing welfare in 62% (Figure 8a; Figure A.9 maps price and surplus effects). These country-level policy effects can be large, often exceeding 25% in absolute value.

The country-level effect of responsive policy on welfare is determined by the extent to which policy amplifies baseline distortions. Figure 8b shows that policy responses induce larger welfare losses the more they amplify distortions on average. In India, for example, pro-consumer policy at baseline is intensified when policy responses to extreme heat shocks. Larger price wedges then reduce efficiency and total welfare. By contrast, policy responses lead to welfare gains for countries like the US and China, where the amplification of baseline distortions is more limited.

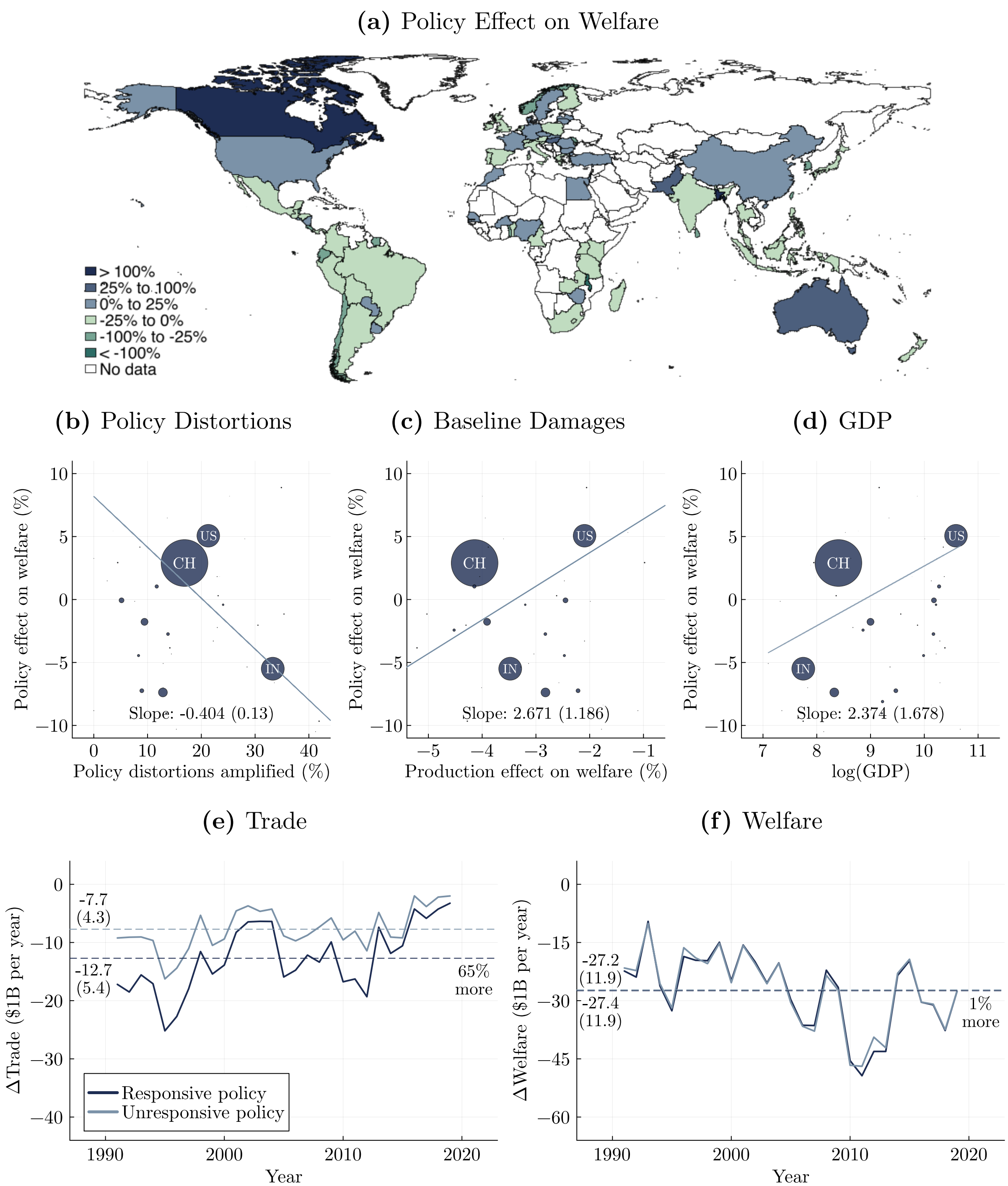
The resulting distributional impact is regressive. Figures 8c and 8d consider impacts on countries by baseline damages and income. Policy responses exacerbate inequality in baseline damages: countries that are most adversely affected by extreme heat shocks are hurt by policy responses, on average, while countries that are least adversely affected are helped. Policy responses also generate welfare losses for the poorest countries and welfare gains for the richest, although this relationship is less precise estimated.

At the global level, policy responses reduce global trade flows but not aggregate welfare. As extreme heat shocks destroy production, the direct effect under unresponsive policy is to reduce trade flows by an average of $7.7B annually (Figure 8e). But the reduction in trade is 65% larger under responsive policy, echoing our motivating example of export bans on Indian wheat. At the same time, policy responses continue to have neutral effects on aggregate welfare (Figure 8f). Policy responses reduce policy distortions for many markets, generating welfare gains that offset welfare losses in markets where distortions are amplified.

Climate Change. Policy responses might also affect future climate damages, which will be much larger than those in our sample. We consider projected extreme heat exposure from 2091 to 2100, drawing on projections from the Geophysical Fluid Dynamics Labo-

to foreign shocks offset these effects, reducing losses in shocked markets and worsening losses in unshocked markets. Similarly, responses by shocked markets worsen losses in shocked markets and reduce losses in unshocked markets, with offsetting effects from responses by unshocked markets.

Figure 8: Heterogeneity and Mechanisms



Panel (a) maps shock-induced changes in welfare under responsive policy, reported as a percentage difference relative to shock-induced changes in welfare under unresponsive policy. We aggregate to the country level by summing welfare across crops and years. Panels (b), (c), and (d) plot the same policy effects on welfare relative to (b) the percentage share of policy distortions that are amplified under responsive policy, (c) shock-induced changes in welfare under unresponsive policy, and (d) log GDP. Points are proportional in size to consumption expenditures. We label the top three: China, India, and the US. Panels (e) and (f) plot shock-induced changes in global trade and welfare over time. Dollars are inflation-adjusted, year-2020 USD. Shocks are observed extreme heat shocks from 1991 to 2019. We report standard errors in parentheses.

ratory's Earth System Model (GFDL-ESM4).[20] Table A.11 converts projected exposure into quartiles and tabulates it against observed exposure. Projected domestic exposure exceeds baseline domestic exposure by one quartile for 60% of country-crop-year markets, with 50% for foreign exposure. Projected and baseline exposure differ by two or more quartiles for 17% of markets.

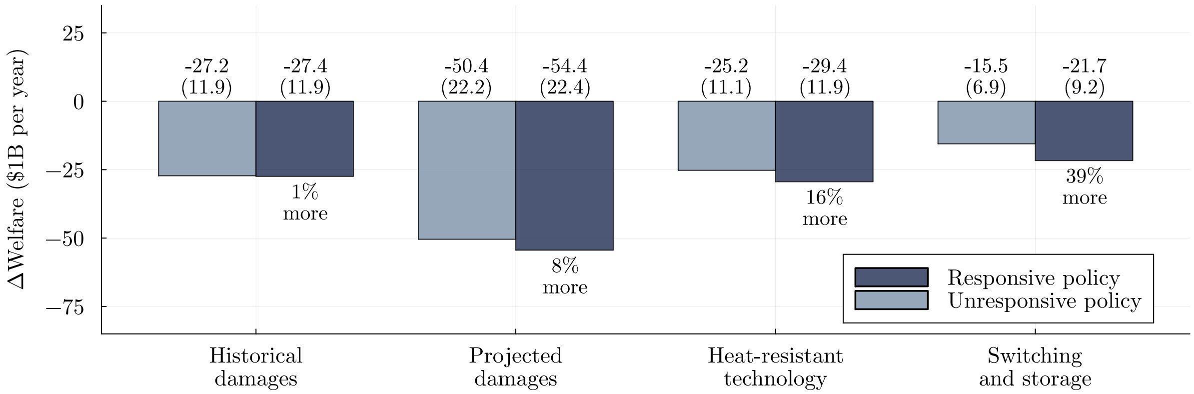
We encounter new challenges in projecting to 2100. First, our baseline analysis relies on short-run elasticities of demand and supply. In simulating climate change, we rely instead on long-run elasticities of $\varepsilon_d = 2.82$ and $\varepsilon_s = 1.46$ based on estimates from Costinot et al. (2016).[21] Second, we do not model or estimate adaptation through technological improvements, which may improve heat resistance and reduce crop losses in the long run. We illustrate this mechanism with a smaller damage function, which encodes production losses that are half as large as those that we estimate in sample. Third, we do not account for adaptation through crop switching and storage. Each is relevant because climate change increases the variance of production and thus encourages investment in switching and storage capacity. This capacity allows farmers to sell more when prices are high and less when prices are low. We illustrate this mechanism with a larger supply elasticity, which is twice as large as the long-run elasticity of Costinot et al. (2016). We compare welfare losses under each scenario to those that we compute in sample.

Figure 9 presents the results. In our historical sample, welfare losses amount to \$27.2B and \$27.4B annually under unresponsive and responsive policy. Policy responses increase welfare losses by only 1% in aggregate, despite meaningful redistributive effects. Under climate change, larger shocks lead to larger annual welfare losses in excess of \$50B. Moreover, policy responses no longer net out in aggregate, instead exacerbating welfare losses by 8% from \$50.4B to \$54.4B. The reason is that climate change disproportionately affects parts of the world that currently implement pro-consumer policies. Policy responses serve to strengthen these policies, magnifying pre-existing distortions and increasing deadweight loss. Table A.11 shows that policy responses increase policy distortions for 47% and 46% of heavily shocked and shocked markets. Even 22% of unshocked markets experience increased policy distortions. Each exceeds the 19% share of markets with increased distortions under historical shocks. Figure A.10 breaks out price and welfare effects by shocked and unshocked markets.

[20] We take central model forecasts from NASA's Global Daily Downscaled Projections, corresponding to the SSP 4.5 pathway for global greenhouse gas concentrations.

[21] We take estimates $\varepsilon_d = \kappa = 2.82$ and $\varepsilon_s = \theta - 1 = 1.46$ from Table 2 in Costinot et al. (2016).

Figure 9: Climate Change and Adaptation



We compute shock-induced changes in welfare under responsive and unresponsive policy. Responsive policy adjusts as estimated, and unresponsive policy is fixed at baseline levels. We report changes in billions of dollars per year relative to baseline levels, and we aggregate by summing across countries, crops, and years. Dollars are inflation-adjusted, year-2020 USD. Historical damages are from observed extreme heat shocks from 1991 to 2019. Projected damages are from projected shocks from GFDL-ESM4 for 2091 to 2100. Our projected damages incorporate long-run demand and supply elasticities from Costinot et al. (2016). Heat-resistant technology recomputes projected damages with a smaller damage function, which encodes production losses that are half as large as those that we estimate in sample. Switching and storage recomputes projected damages with a smaller damage function and a larger supply elasticity, which is twice as large as the long-run elasticity of Costinot et al. (2016). We report standard errors in parentheses.

Welfare losses are smaller in our adaptation scenarios, but the policy effects grow larger. A weaker damage function directly blunts the impacts of extreme heat exposure, but the effect of endogenous policy grows: policy responses worsen welfare losses by 16%. A higher elasticity of supply allows unshocked producers to expand production more forcefully following losses in shocked markets. Again, welfare losses fall in both scenarios, but policy responses exacerbate welfare losses by 39%. Thus, adaptation may reduce welfare losses, but policy effects remain salient.

6 Conclusion

While international leaders proclaim that "food security rests on trade" (Gurria and da Silva, 2019), a growing number of examples suggest that governments are willing to alter food policy and restrict trade in response to environmental shocks. We study how this phenomenon affects the global response to climate change. We compile comprehensive data on agricultural policy interventions and extreme heat exposure since 1980. We find that domestic heat shocks lead governments to systematically shift policy in a pro-consumer direction. Foreign extreme heat shocks have the opposite effect and stabilize the global impact of temperature on policy. The results are most pronounced during elections, when politicians may be especially attuned to constituent demands. These results can be rationalized by a model in which trade policy is a tool to achieve redistribution across different groups in society.

Finally, we quantify how responsive agricultural policy changes the incidence and overall effect of extreme heat shocks. In shocked markets, responsive policy dampens price spikes by 18%, shielding local consumers against 21% of potential losses but more than doubling losses for producers and increasing losses for foreign consumers by 32%. Welfare losses from these policy responses fall disproportionately on countries that are poorest and most adversely affected by global warming. Extrapolating our results to study end-of-century climate change, we find that responsive policy amplifies total damages by 8% because policy responses increase deadweight loss on net. Climate change affects economic policy, and economic policy in turn affects the consequences of climate change.

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Online Appendix: Food Policy in a Warming World

A Proofs

A.1 Proof of Lemma 1

We first solve for each household's choices. Given quasi-linearity, we can substitute for money z_i in the household's objective and write

$$\mathcal{U}_i = \mu_i^{\frac{1}{\varepsilon_d}} \frac{q_i^{1-\frac{1}{\varepsilon_d}}}{1-\frac{1}{\varepsilon_d}} + p(y_i - q_i) + T_i - \omega^{-\frac{1}{\varepsilon_s}} \psi_i^{-\frac{1}{\varepsilon_s}} \frac{y_i^{1+\frac{1}{\varepsilon_s}}}{1+\frac{1}{\varepsilon_s}} \tag{A.1}$$

The first-order condition for agricultural consumption is

$$\mu_i^{\frac{1}{\varepsilon_d}} q_i^{-\frac{1}{\varepsilon_d}} = p \qquad \Rightarrow \qquad q_i = \mu_i p^{-\varepsilon_d} \tag{A.2}$$

The first-order condition for agricultural production is:

$$\omega^{-\frac{1}{\varepsilon_s}} \psi_i^{-\frac{1}{\varepsilon_s}} y_i^{\frac{1}{\varepsilon_s}} = p \qquad \Rightarrow \qquad y_i = \omega \psi_i p^{\varepsilon_s} \tag{A.3}$$

We next aggregate the "demand side" of the economy. Total demand for the agricultural good is $\sum_{i=1}^N q_i = (\sum_{i=1}^N \mu_i) p^{-\varepsilon_d} = p^{-\varepsilon_d}$, where the second equality uses our normalization $\sum_{i=1}^N \mu_i = 1$. Moreover, as claimed, each consumer i's share of consumption is $\frac{q_i}{\sum_{i=1}^N q_i} = \mu_i$. The component of households' payoff deriving directly from consumption is

$$\mathcal{C}_i := \mu_i^{\frac{1}{\varepsilon_d}} \frac{q_i^{1-\frac{1}{\varepsilon_d}}}{1-\frac{1}{\varepsilon_d}} - p q_i = \frac{1}{1-\frac{1}{\varepsilon_d}} \mu_i p^{1-\varepsilon_d} - \mu_i p^{1-\varepsilon_d} = \frac{\mu_i}{\varepsilon_d - 1} p^{1-\varepsilon_d} \tag{A.4}$$

We next aggregate the "supply side" of the economy. Total production of the agricultural good is $\sum_{i=1}^N y_i = \omega(\sum_{i=1}^N \psi_i) p^{\varepsilon_s} = \omega p^{\varepsilon_s}$, where the second equality uses our normalization $\sum_{i=1}^N \psi_i = 1$. Moreover, as claimed, each consumer i's share of production is $\frac{y_i}{\sum_{i=1}^N y_i} = \psi_i$. The component of households' payoff deriving directly from production is.

$$\mathcal{P}_i := p y_i - (\omega \psi_i)^{-\frac{1}{\varepsilon_s}} \frac{y_i^{1+\frac{1}{\varepsilon_s}}}{1+\frac{1}{\varepsilon_s}} = \frac{\omega \psi_i}{1+\varepsilon_s} p^{1+\varepsilon_s} \tag{A.5}$$

We next derive consumer and producer surplus. We define consumer surplus in the economy, at domestic price p^*, as the area under the demand curve between p^* and some arbitrarily large reference price $\bar{p}$:

$$\begin{aligned}\mathcal{C} &= \int_{p^*}^{\bar{p}} \sum_{i=1}^{N} \mu_i p^{-\varepsilon_d}\,\mathrm{d}p = \sum_{i=1}^{N} \int_{p^*}^{\bar{p}} \mu_i p^{-\varepsilon_d}\,\mathrm{d}p \\ &= \sum_{i=1}^{N} \left[\frac{1}{1-\varepsilon_d}\mu_i p^{1-\varepsilon_d}\right]_{p^*}^{\bar{p}} = \frac{1}{\varepsilon_d - 1} p^{1-\varepsilon_d} + K\end{aligned} \tag{A.6}$$

where the constant $K = \frac{1}{1-\varepsilon_d}\bar{p}^{1-\varepsilon_d}$ is finite an does not depend on equilibrium outcomes. Thus, for all i, $\mathcal{C}_i = \mu_i \mathcal{C} - \mu_i K$.

A similar calculation yields that producer surplus is

$$\begin{aligned}\mathcal{P} &= \int_{0}^{p^*} \sum_{i=1}^{N} \psi_i \omega p^{\varepsilon_s}\,\mathrm{d}p = \sum_{i=1}^{N} \int_{0}^{p^*} \psi_i \omega p^{\varepsilon_s}\,\mathrm{d}p \\ &= \sum_{i=1}^{N} \left[\frac{1}{1+\varepsilon_s}\psi_i \omega p^{1+\varepsilon_s}\right]_{0}^{p^*} = \frac{\omega}{1+\varepsilon_s} p^{1+\varepsilon_s}\end{aligned} \tag{A.7}$$

Thus, for all i, $\mathcal{P}_i = \psi_i \mathcal{P}$.

We finally show the equivalence of the social welfare function, $\mathcal{W} = \sum_{i=1}^{N} \lambda_i \mathcal{U}_i$:

$$\begin{aligned}\mathcal{W} &= \sum_{i=1}^{N} \lambda_i (\mathcal{C}_i + \mathcal{P}_i + T_i) = \sum_{i=1}^{N} \lambda_i (\mu_i \mathcal{C} - \mu_i K + \psi_i \mathcal{P} + \xi_i \mathcal{G}) \\ &= \left(\sum_{i=1}^{N} \mu_i \lambda_i\right) \mathcal{C} + \left(\sum_{i=1}^{N} \psi_i \lambda_i\right) \mathcal{P} + \left(\sum_{i=1}^{N} \xi_i \lambda_i\right) \mathcal{G} - \left(\sum_{i=1}^{N} \mu_i \lambda_i\right) K \\ &= \lambda^C \mathcal{C} + \lambda^P \mathcal{P} + \lambda^G \mathcal{G} + \tilde{K}\end{aligned} \tag{A.8}$$

where the second equality in the first line uses the representations of individual payoffs derived above as well as the transfer rule. This is, up to the irrelevant constant $\tilde{K}$ defined in the last line, the same government objective in Equation 4.1. This concludes the proof.

A.2 Proof of Proposition 1

We prove Propositions 1 and 2 in a generalized model that allows us to study net exporters and importers together. In particular, we assume that net exports are described by the function

$$X(p, \omega') = X_0(\omega') p^{-\varepsilon_x} \tag{A.9}$$

where $X_0 : \mathbb{R} \to \mathbb{R}$ is an increasing function. We consider two cases. First, $X_0 > 0$, $\varepsilon_x > 0$, $\varepsilon_d < \varepsilon_x < \infty$, and $\varepsilon_x > 1$. This is the case of a net exporter described in the main text. Second, $X_0 < 0$, $\varepsilon_x < 0$, $\varepsilon_s < -\varepsilon_x < \infty$, and $-\varepsilon_x > 1$. In this case, $M(p, \omega') := -X(p, \omega') > 0$ is an isoleastic foreign supply curve for imports. The additional assumptions encode that import supply is more elastic than the domestic supply, but not infinitely so. In all cases, an increase in the shock ω' corresponds to higher net demand or lower net supply abroad. Finally, for convenience, we re-parameterize the problem so that the choice variable is the additive price wedge τ which satisfies $p^* - \tau = p^*/(1+\alpha)$. Program 4.1 becomes

$$\begin{aligned} \tau^* \in \underset{\tau \in (-\infty, p^*]}{\arg\max} & \left\{ \lambda^C \int_{p^*}^{\infty} Q(p)\, \mathrm{d}p + \lambda^P \int_0^{p^*} Y(p, \omega)\, \mathrm{d}p - \lambda^G \tau X\left(p^* - \tau, \omega'\right) \right\} \\ \text{s.t. } & p^* = P^*(\tau, \omega, \omega') \end{aligned} \tag{A.10}$$

where, in some abuse of notation, we still use P^* to denote the equilibrium mapping from policy and shocks to domestic prices. We proceed by deriving the optimal tariff under the assumption that it is interior; at the end, we show that the assumption $\varepsilon_x \notin (0, -1)$ is sufficient to guarantee interiority.

We first derive $\partial p / \partial \tau$ by implicitly differentiating market clearing:

$$\frac{\partial Q(p)}{\partial p}\Big|_{p=p^*} \frac{\partial p^*}{\partial \tau} = \frac{\partial Y(p, \omega)}{\partial p}\Big|_{p=p^*} \frac{\partial p^*}{\partial \tau} - \frac{\partial X(p, \omega')}{\partial p}\Big|_{p=p^*-\tau} \left(\frac{\partial p^*}{\partial \tau} - 1 \right) \tag{A.11}$$

Re-arranging, and suppressing the evaluations, we obtain

$$\frac{\partial p^*}{\partial \tau} = \frac{\frac{\partial X(p,\omega')}{\partial p}}{\frac{\partial Q(p)}{\partial p} - \frac{\partial Y(p,\omega)}{\partial p} + \frac{\partial X(p,\omega')}{\partial p}} = \frac{\varepsilon_x (1-r)}{-\varepsilon_d \left(1 - \frac{\tau}{p^*}\right) - \left(r \varepsilon_s \left(1 - \frac{\tau}{p^*}\right) - (1-r)\varepsilon_x \right)} \tag{A.12}$$

where we define the elasticities $\varepsilon_z = \frac{\partial z}{\partial p} \frac{p}{z}$, for $z \in \{x, y, m\}$ and with all prices evaluated in equilibrium.

The necessary first-order condition of Program A.10 in τ is

$$0 = \frac{\partial P^*(\tau, \omega, \omega')}{\partial \tau} \left(-\lambda^C x + \lambda^P y \right) - \lambda^G x - \lambda^G \tau \frac{\partial X(p^* - \tau, \omega')}{\partial p} \left(\frac{\partial P^*(\tau, \omega, \omega')}{\partial \tau} - 1 \right) \tag{A.13}$$

This re-arranges to

$$\tau = \frac{\frac{\partial p^*(\tau)}{\partial \tau}\left(\lambda^P y - \lambda^C q\right) - \lambda^G x}{-\lambda^G \frac{\partial X(p^*(\tau)-\tau)}{\partial p}\left(1 - \frac{\partial p^*(\tau)}{\partial \tau}\right)} \tag{A.14}$$

Using our expression for $\frac{\partial p^*}{\partial \tau}$ and expressing $\frac{\partial X}{\partial p}$ as an elasticity, we obtain

$$\tau = \frac{\frac{\varepsilon_x(1-r)}{-\varepsilon_d\left(1-\frac{\tau}{p^*}\right)-\left(r\varepsilon_s\left(1-\frac{\tau}{p^*}\right)-(1-r)\varepsilon_x\right)}\left(\lambda^P y - \lambda^C q\right) - \lambda^G x}{\left(1-\frac{\tau}{p^*}\right)\lambda^G\left(\varepsilon_x \frac{X(p^*-\tau)}{p^*-\tau}\right)\frac{\varepsilon_d - r\varepsilon_s}{-\varepsilon_d\left(1-\frac{\tau}{p^*}\right)-\left(r\varepsilon_s\left(1-\frac{\tau}{p^*}\right)-(1-r)\varepsilon_x\right)}} \tag{A.15}$$

Cancelling alike terms in the numerator and denominator, we simplify this to

$$\frac{\tau}{p^*} = \frac{s\left(\lambda^P Y(p^*(\tau)) - \lambda^C Q(p^*(\tau))\right)}{\lambda^G M(p^*(\tau)-\tau)((1-s)\varepsilon_s + \varepsilon_d)} - \frac{-\varepsilon_d\left(1-\frac{\tau}{p^*}\right) - \left((1-s)\varepsilon_s\left(1-\frac{\tau}{p^*}\right) - s\varepsilon_x\right)}{-\varepsilon_x((1-s)\varepsilon_s + \varepsilon_d)} \tag{A.16}$$

Re-arranging and simplifying, we obtain

$$\frac{\tau}{p^*} = \frac{-\varepsilon_x}{1-\varepsilon_x}\left(\frac{\lambda^P r + \lambda^G(1-r) - \lambda^C}{\lambda^G(\varepsilon_s r + \varepsilon_d)}\right) + \frac{1}{1-\varepsilon_x} \tag{A.17}$$

Equation 4.4 follows by defining $\alpha = \frac{\tau}{p^*-\tau}$.

We next check that the conjectured solution lies in the correct domain, or $\alpha > -1$. To do this, we write the condition

$$-\frac{1}{\varepsilon_x}\left(\frac{\lambda^G\left(r\varepsilon_s + \varepsilon_d\right) + \varepsilon_x\left(\lambda^P r + \lambda^G(1-r) - \lambda^C\right)}{\lambda^G\left(r\varepsilon_s + \varepsilon_d\right) - \left(\lambda^P r + \lambda^G(1-r) - \lambda^C\right)}\right) > -1 \tag{A.18}$$

Multiplying both sides by $-\varepsilon_x(1-r) > 0$, we obtain

$$\frac{(1-r)\lambda^G\left(r\varepsilon_s + \varepsilon_d\right) + (1-r)\varepsilon_x\left(\lambda^P r + \lambda^G(1-r) - \lambda^C\right)}{\lambda^G\left(r\varepsilon_s + \varepsilon_d\right) - \left(\lambda^P r + \lambda^G(1-r) - \lambda^C\right)} > -\varepsilon_x(1-r) \tag{A.19}$$

We now split cases. Consider first the case in which the denominator of the left-hand-side is positive. Then, multiplying both sides by the denominator and simplifying, the relevant condition simplifies to $1-r > (1-r)\varepsilon_x$. In the exporting case, this follows from $r > 1$ ($y > q$) and $\varepsilon_x > 1$. In the importing case, this follows from $r < 1$ and $\varepsilon_x < 0$.

Consider next the case in which the denominator of Equation A.19 is negative. In this case, the relevant condition is $1-r < -(1-r)\varepsilon_x$. In the importing case, this re-arranges to $-\varepsilon_x > 1$, which was assumed. In the exporting case, this is immediate from $\varepsilon_x > 0$.

We finally show the comparative statics by direct calculation:

$$\begin{aligned}
\frac{\partial \alpha^*}{\partial \lambda^C} &= \frac{1-\varepsilon_x}{\varepsilon_x} \frac{(\varepsilon_d + r\varepsilon_s)\lambda^G}{(\lambda^C + (\varepsilon_d - (1-r) + r\varepsilon_s)\lambda^G - r\lambda^P)^2} \leq 0 \\
\frac{\partial \alpha^*}{\partial \lambda^P} &= -\frac{1-\varepsilon_x}{\varepsilon_x} \frac{\lambda^G r(r\varepsilon_s + \varepsilon_d)}{(\lambda^C + (\varepsilon_d - (1-r) + r\varepsilon_s)\lambda^G - r\lambda^P)^2} \geq 0
\end{aligned} \tag{A.20}$$

where, in both inequalities, we use that $\varepsilon_x \notin (0,1)$, so $(1-\varepsilon_x)/\varepsilon_x < 0$.

A.3 Proof of Proposition 2

In the arguments below, we let $s = 1 - r = -\frac{x}{q}$ denote the import share. We first state and prove two Lemmas:

Lemma 2. *A pair (α^*, s^*) constitutes an equilibrium if*

$$\begin{aligned}
\alpha^* &= A(s^*) \\
s^* &= S(\alpha^*, \omega, \omega')
\end{aligned} \tag{A.21}$$

where (i) S decreases in α, (ii) S increases in ω, (iii) S increases in ω', and (iv) $\alpha = A(s^*)$ crosses $\alpha = S^{-1}(s^*; \omega, \omega')$ once from below.

Proof. Property (i): From market clearing,

$$Q(p^*) = Y(p^*, \omega) - X\left(\frac{p^*}{1+\alpha}, \omega'\right) \tag{A.22}$$

and the fact that M is decreasing, Y is increasing, and Q is decreasing, it is immediate that p^* increases in α. Moreover, since Y increases in p and Q decreases in p, we have that $s = 1 - Y/Q$ decreases in α. Differentiability follows from the differentiability of Y, Q and P^*.

Property (ii): Using market clearing, an equivalent expression for S is

$$S(\alpha, \omega, \omega') = -\frac{X\left(\frac{P^*(\alpha,\omega,\omega')}{1+\alpha}, \omega'\right)}{Q(P^*(\alpha, \omega, \omega'))} \tag{A.23}$$

Consider some $\omega_1 > \omega_0$. Consider first the case in which $x > 0$ and therefore $s < 0$. then,

$$\frac{S(\alpha,\omega_1,\omega')}{S(\alpha,\omega_0,\omega')} = \frac{\left(\frac{P^*(\alpha,\omega_1,\omega')}{P^*(\alpha,\omega_0,\omega')}\right)^{-\varepsilon_x}}{\left(\frac{P^*(\alpha,\omega_1,\omega')}{P^*(\alpha,\omega_0,\omega')}\right)^{-\varepsilon_d}} = \left(\frac{P^*(\alpha,\omega_1,\omega')}{P^*(\alpha,\omega_0,\omega')}\right)^{\varepsilon_d-\varepsilon_x} < 1 \tag{A.24}$$

Where the inequality follows from observing that $P^*(\alpha,\omega_1,\omega') > P^*(\alpha,\omega_0,\omega')$ (P^* increases in ω) and $\varepsilon_d - \varepsilon_x < 0$ (foreign demand is more price elastic than domestic demand). Therefore, since $s < 0$, $S(\alpha,\omega_1,\omega') > S(\alpha,\omega_0,\omega')$ as desired. Next, consider the case in which $x < 0$ and therefore $s > 0$. Then, we have

$$\frac{S(\alpha,\omega_1,\omega')}{S(\alpha,\omega_0,\omega')} == \left(\frac{P^*(\alpha,\omega_1,\omega')}{P^*(\alpha,\omega_0,\omega')}\right)^{\varepsilon_d-\varepsilon_x} > 1 \tag{A.25}$$

where the inequality follows from $P^*(\alpha,\omega_1,\omega') > P^*(\alpha,\omega_0,\omega')$ (P^* increases in ω) and $\varepsilon_x < -1$ and therefore $\varepsilon_d - \varepsilon_x > 1$ (foreign supply is upward sloping). Therefore, since $s > 0$, $S(\alpha,\omega_1,\omega') > S(\alpha,\omega_0,\omega')$ as desired.

Property (iii): This follows from the same logic as the comparative static in α: a decrease in ω' perturbs market clearing in the same way as an increase in α.

Property (iv): By direct calculation,

$$\frac{\partial S}{\partial \alpha} = -\frac{(1-s)(-s\varepsilon_x)(\varepsilon_s+\varepsilon_d)}{(1-s)\varepsilon_s - s\varepsilon_x + \varepsilon_d}\frac{1}{(1+\alpha)} < 0 \tag{A.26}$$

where the inequality uses $s\varepsilon_x < 0$ and $\alpha > -1$ (interiority). If $\frac{\mathrm{d}A^*}{\mathrm{d}s} \geq 0$, then the claim follows from the fact that the government's problem is globally concave and there must exist a solution. If $\frac{\mathrm{d}A^*}{\mathrm{d}s} < 0$, then we make the following "boundary conditions" argument. First, $\lim_{s\to 1} S^{-1}(s^*;\omega,\omega') = -\infty$: that is, the policy that supports an import share of 1 is unbounded consumer assistance. Second, $\lim_{s\to 1} A(s) > -\infty$: an import share of 100% corresponds to a well-defined policy. Because of the uniqueness of the optimal policy and concavity of the objective, A and S^{-1} must cross exactly once. If A crossed S^{-1} once from above, and $A(1) > \lim_{s\to 1} S^{-1}(1)$, then it would have to be the case, by continuity, that they cross at least once more. This contradicts the uniqueness of the optimal policy.

□

Lemma 3 (Relative Assistance and Import Shares)**.** *The following statements are true:*

1. *If the government is revenue-focused, or* $\varepsilon_s(\lambda^C - \lambda^G) + \varepsilon_d(\lambda^P - \lambda^G) < 0$*, then* $A^{*'} > 0$*,*

or higher import shares are associated with higher producer assistance.

2. *If the government is redistribution-focused, or* $\varepsilon_s(\lambda^C - \lambda^G) + \varepsilon_d(\lambda^P - \lambda^G) > 0$*, then* $A^{*'} < 0$*, or higher import shares are associated with higher consumer assistance.*
3. *If the government is neutral, or* $\varepsilon_s(\lambda^C - \lambda^G) + \varepsilon_d(\lambda^P - \lambda^G) = 0$*, then* $A^{*'} = 0$*, or assistance is invariant to the import share.*

Proof. By direct calculation, we have that

$$\frac{\partial A^*(s)}{\partial s} = \frac{\varepsilon_x - 1}{\varepsilon_x} \frac{\left(\lambda^G(\varepsilon_s + \varepsilon_d) - \lambda^C \varepsilon_s - \lambda^P \varepsilon_d\right) \lambda_G}{\left(\lambda^G\left((1-s)\varepsilon_s + \varepsilon_d\right) + \left(\lambda^P(1-s) + \lambda^G s - \lambda^C\right)\right)^2} \tag{A.27}$$

where we observe that $\frac{\varepsilon_x - 1}{\varepsilon_x} > 0$ under our maintained assumptions. Thus, the sign of this derivative is determined by the sign of $\lambda^G(\varepsilon_s + \varepsilon_d) - \lambda^C \varepsilon_s - \lambda^P \varepsilon_d$, which is exactly the condition for revenue versus constituent focus, as indicated. The additional claims follow from observing that $\alpha = A^*(s)$ must hold in any equilibrium. Thus if α^* increases comparing the unique equilibrium associated with two different parameter values, then s decreases; and if α^* increases, then s decreases. $\square$

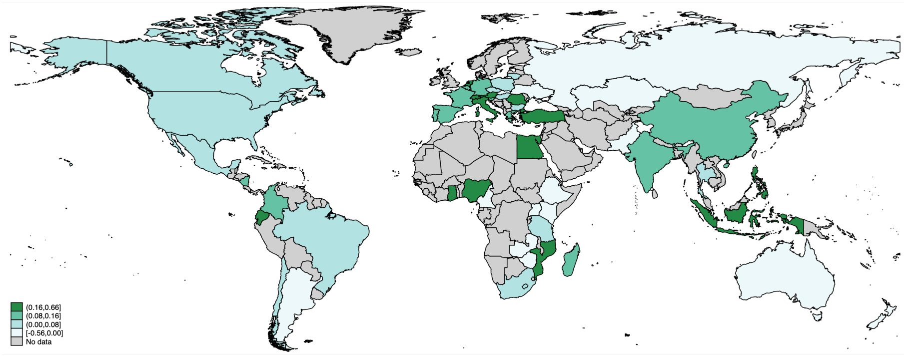
We prove the cases in turn. For all cases, we observe that for $\omega_1 \geq \omega_0$ and $\omega_1' \geq \omega_0'$, then $S(\alpha, \omega_1, \omega_1') \geq S(\alpha, \omega_0, \omega_0')$ for all α. We let α_1^*, α_0^* denote the equilibrium policy in each case. We observe that $\alpha \mapsto S^{-1}(s, \omega, \omega')$ is decreasing for any ω, ω'.

1. Since $A(s)$ is strictly decreasing (Lemma 3), then $f(s) = S^{-1}(s, \omega_1, \omega_1') - A^*(s)$ crosses the origin once from above and $f(s_{m,0}^*) \geq 0$. Moreover, for any equilibrium $s_{m,1}^*$, $f(s_{m,1}^*) = 0$. Therefore, $s_{m,1}^* \geq s_{m,0}^*$, provided that an equilibrium exists (which has been established earlier) and is unique. Since A^* is decreasing, then $\alpha_1^* = A(s_{m,1}^*) \leq \alpha_0^*$.
2. Since $A(s)$ is strictly increasing (Lemma 3), then $f(s) = S^{-1}(s, \omega_1, \omega_1') - A^*(s)$ is a decreasing function and $f(s_{m,0}^*) \geq 0$. Moreover, for any equilibrium $s_{m,1}^*$, $f(s_{m,1}^*) = 0$. Therefore, $s_{m,1}^* \geq s_{m,0}^*$, provided that an equilibrium exists (which has been established earlier). Since A^* is increasing, then $\alpha_1^* = A(s_{m,1}^*) \geq \alpha_0^*$.

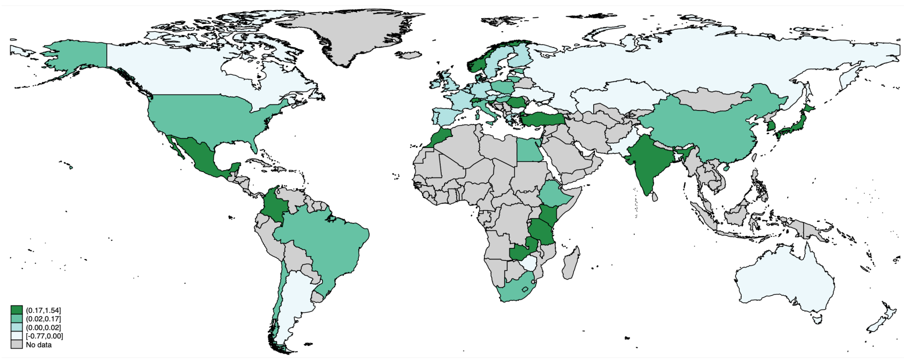
B Additional Figures and Tables

Figure A.1: Average Nominal Rates of Assistance for Select Crops

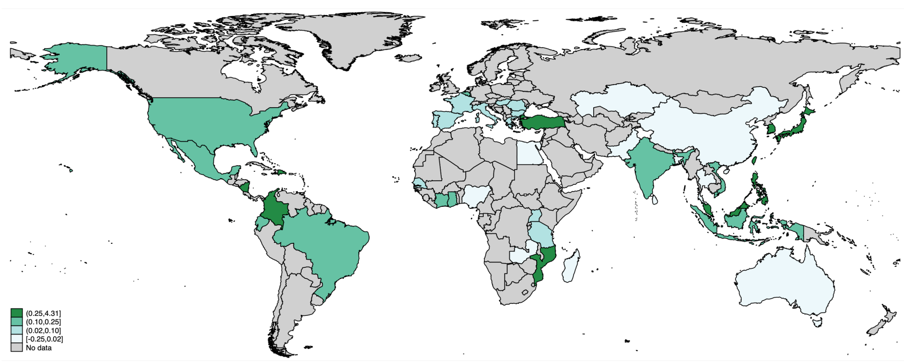
(a) Maize



(b) Wheat



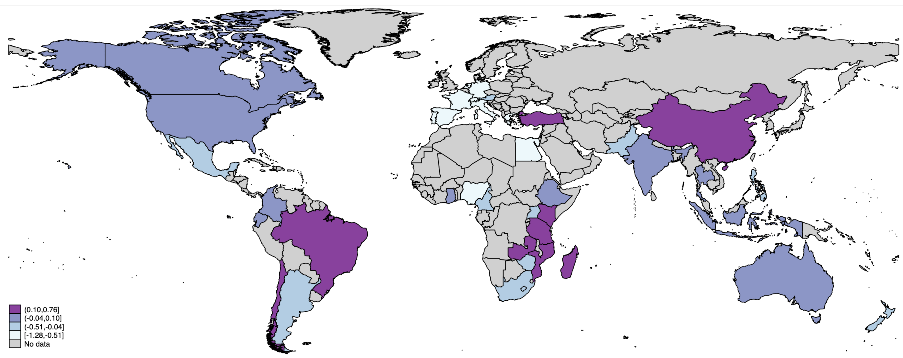
(c) Rice



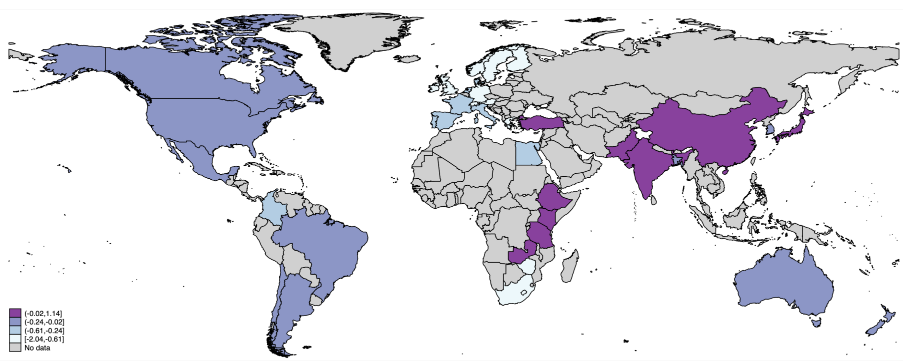
This figure displays the average value from 2001 to 2010 of the nominal rate of assistance (NRA) for maize, wheat, and rice. Countries are color-coded by quartile, where darker colors correspond to larger values.

Figure A.2: Changes in Nominal Rates of Assistance for Select Crops

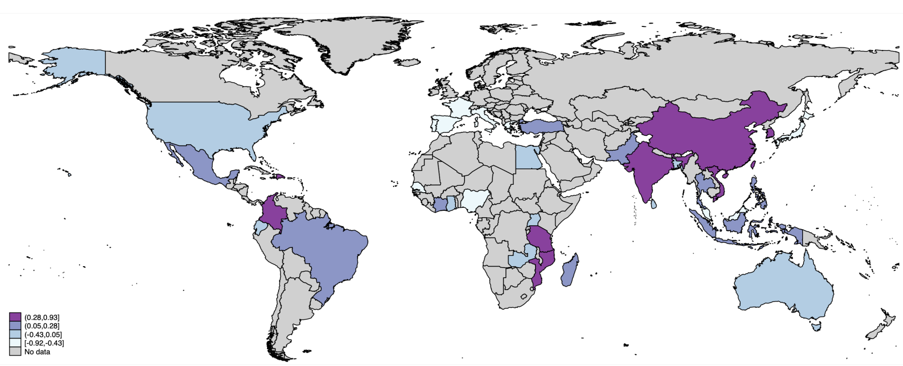
(a) Maize



(b) Wheat



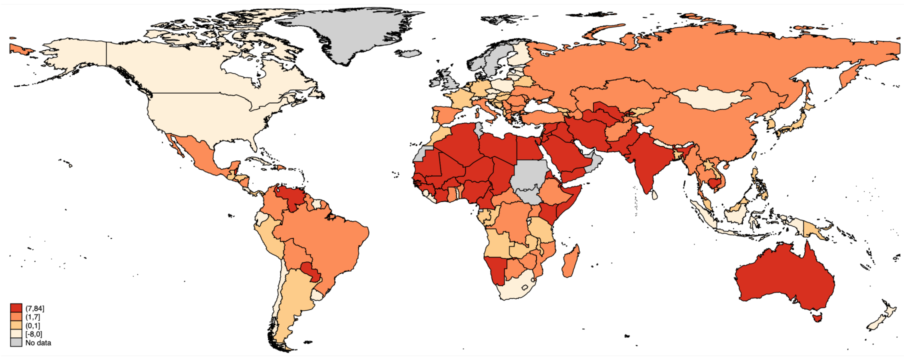
(c) Rice



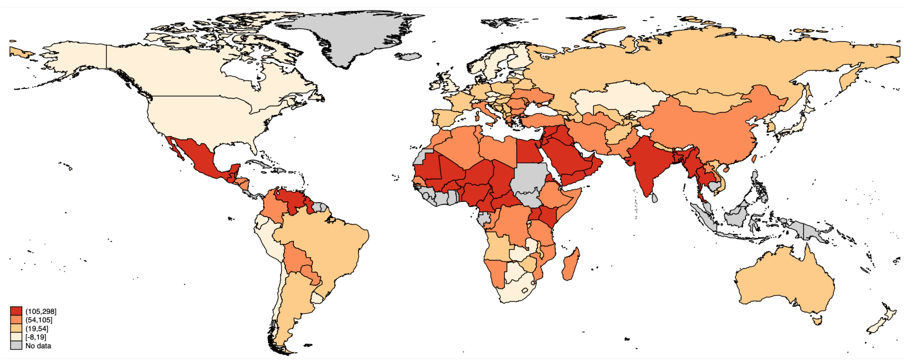
This figure displays the change in NRA for maize, wheat, and rice between the 1980s (average value in the decade) and the 2000s (average value in the decade). Countries are color-coded by quartile, where darker colors correspond to larger values.

Figure A.3: Global Changes in Extreme Heat for Select Crops

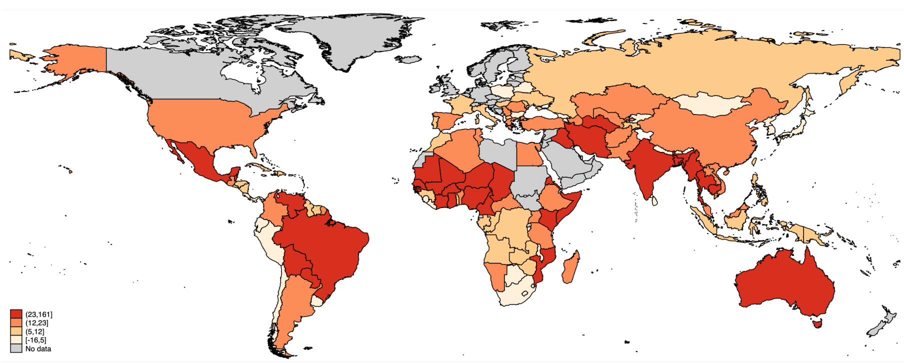
(a) Maize



(b) Wheat

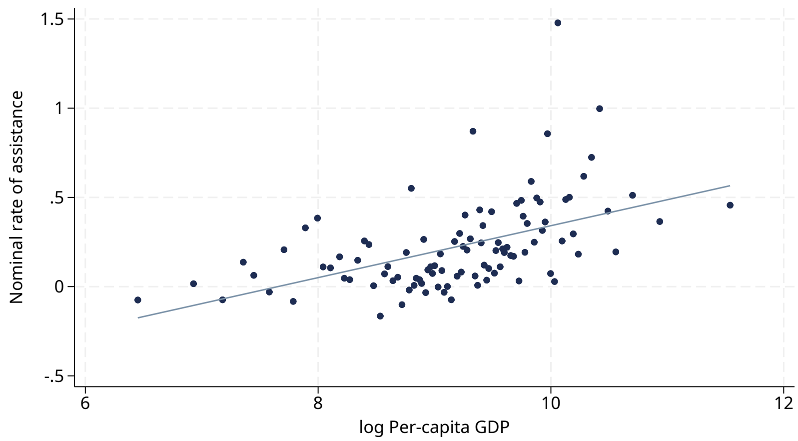


(c) Rice



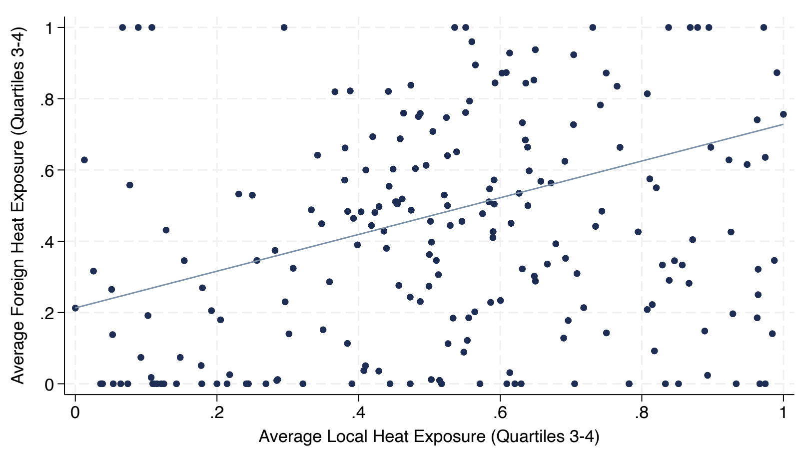
This figure displays the change in extreme heat exposure for maize, wheat, and rice between the 1980s (average value in the decade) and the 2010s (average value in the decade). The units are killing degree days above the critical temperature threshold (see Equation 2.2) per year. Countries are color-coded by quartile, where darker colors correspond to larger values.

Figure A.4: Relationship Between Income and Policy Distortions



This figure displays a binned scatter plot of the relationship between the average nominal rate of assistance over the sample and log of per capita GDP (also averaged over the sample), after absorbing crop fixed effects. The unit of observation is a market or country-crop pair ($N = 620$). The coefficient estimate along with the t-statistic, based on standard errors clustered by country, are reported below the figure.

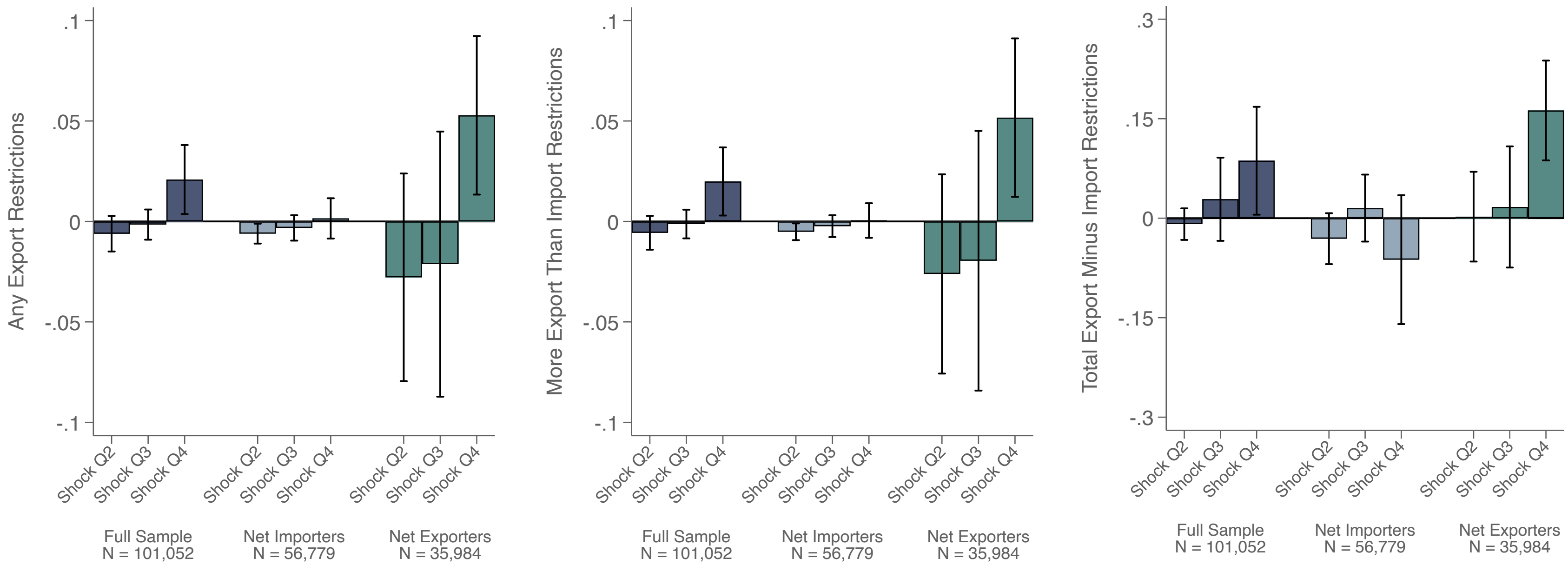
Figure A.5: Relationship Between Domestic and Foreign Extreme Heat Exposure



This figure displays a binned scatter plot of the relationship between average exposure of each market to high levels of domestic extreme heat (third or fourth quartiles) with average exposure of each market to high levels of foreign (trade-weighted) extreme heat (third or fourth quartiles). The unit of observation is a market or country-crop pair ($N = 620$). The coefficient estimate along with the t-statistic, based on standard errors clustered by crop, are reported below the figure.

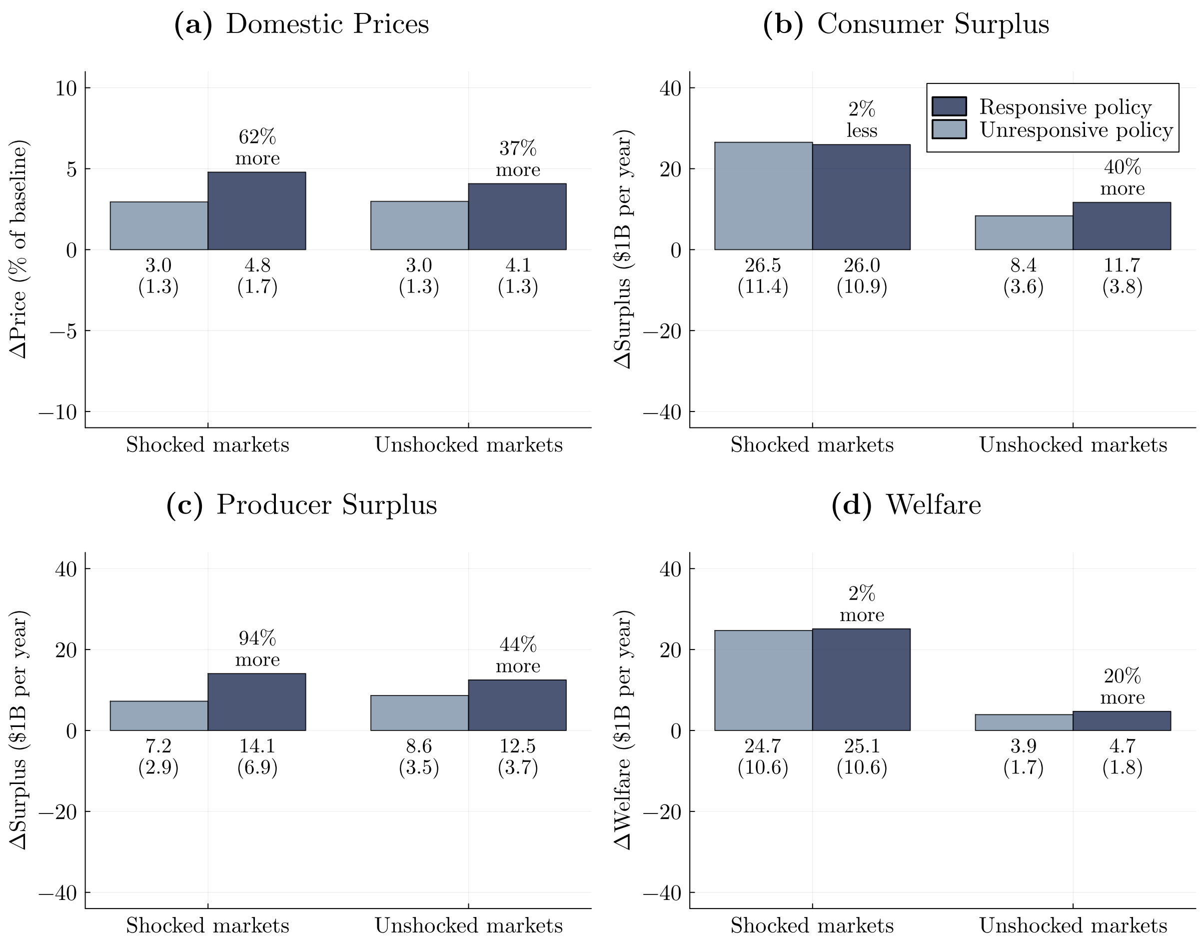
Figure A.6: Effects of Extreme Heat on Trade Disruptions

(a) Export Restrictions **(b)** More Export Than Import Restrictions **(c)** Export Minus Import Restrictions



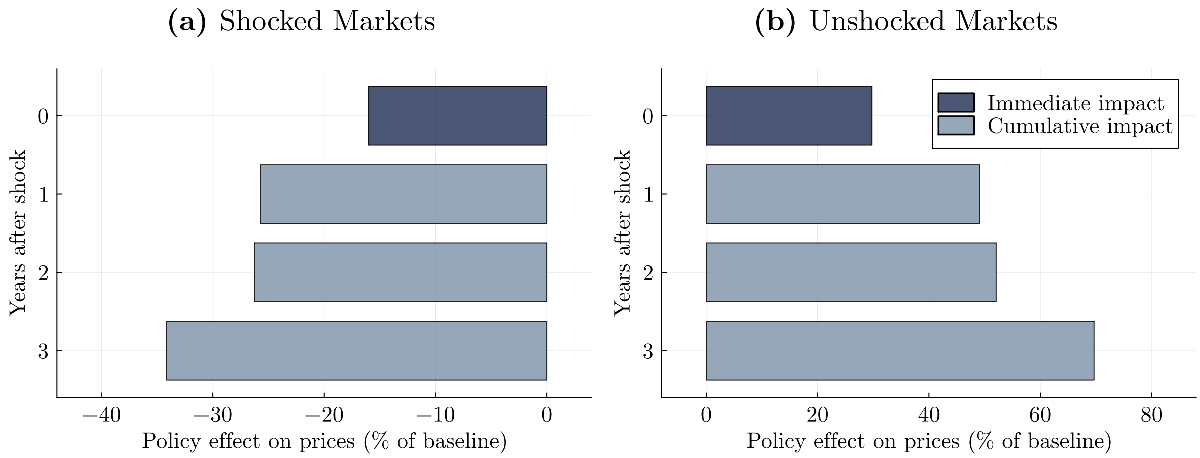
This figure displays the relationship between quartiles of extreme heat exposure and crop-specific policy interventions measured using the Global Trade Alert (GTA) database (https://www.globaltradealert.org/). The unit of observation is a country-pair-crop-year and all specifications include fixed effects at the origin-crop, crop-year, and origin-destination-year levels. In Figure A.6a the outcome variable is an indicator that equals one if there are any export-restricting policies; in Figure A.6b it is an indicator that equals one if there are more export-restricting than import-restricting policies; and in Figure A.6c it is the total number of export-restricting policies minus the total number of import-restricting policies. Since the GTA database begins in 2008, the sample period for all estimates is 2008-2019. We report 90% confidence intervals.

Figure A.7: Effects of Responsive Policy on Dispersion



We compute standard deviations of shock-induced changes across markets and time periods under responsive and unresponsive policy (cf. Figure 7, which shows means of the same distributions). Shocks are observed extreme heat shocks from 1991 to 2019. Responsive policy adjusts as estimated, and unresponsive policy is fixed at baseline levels. We aggregate over countries, crops, and years as follows. For domestic prices, we compute Stone price indices, which weight by expenditure shares, and we report percentage changes relative to baseline prices. For consumer surplus, producer surplus, and welfare, we compute sums and report changes in billions of dollars per year relative to baseline levels. Dollars are inflation-adjusted, year-2020 USD. We report effects separately for shocked markets, which experience domestic extreme heat shocks (34% of markets), and for unshocked markets, which do not (66% of markets). We report standard errors in parentheses.

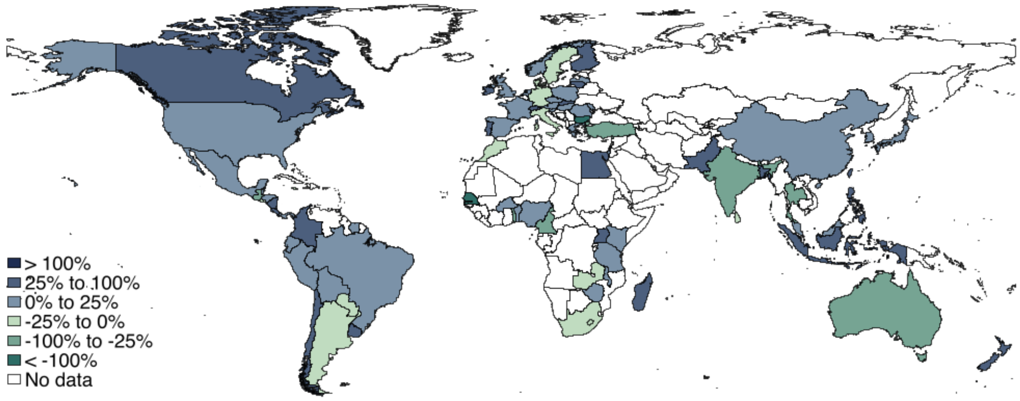
Figure A.8: Policy Dynamics



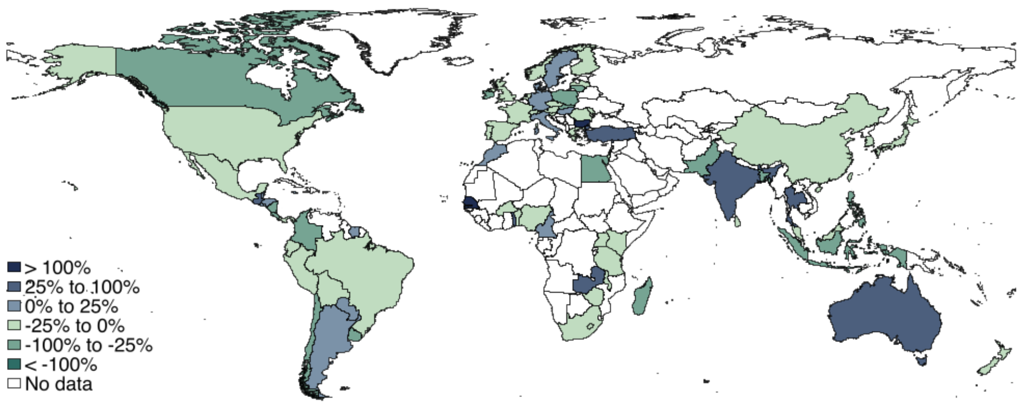
We compute shock-induced changes in domestic prices under responsive policy, reported as a percentage difference relative to shock-induced changes in welfare under unresponsive policy. Shocks are observed extreme heat shocks from 1991 to 2019. We allow for lagged effects in estimation, and we report cumulative effects over time. The immediate impact captures the contemporaneous effect of shocks, which we simulate as one-time shocks. Cumulative impacts incorporate lagged effects in the years that follow. We aggregate across countries, crops, and years by computing Stone price indices, which weight by expenditure shares. We report effects separately for shocked markets, which experience domestic extreme heat shocks (34% of markets), and for unshocked markets, which do not (66% of markets). We report standard errors in parentheses.

Figure A.9: Heterogeneity in Policy Effects

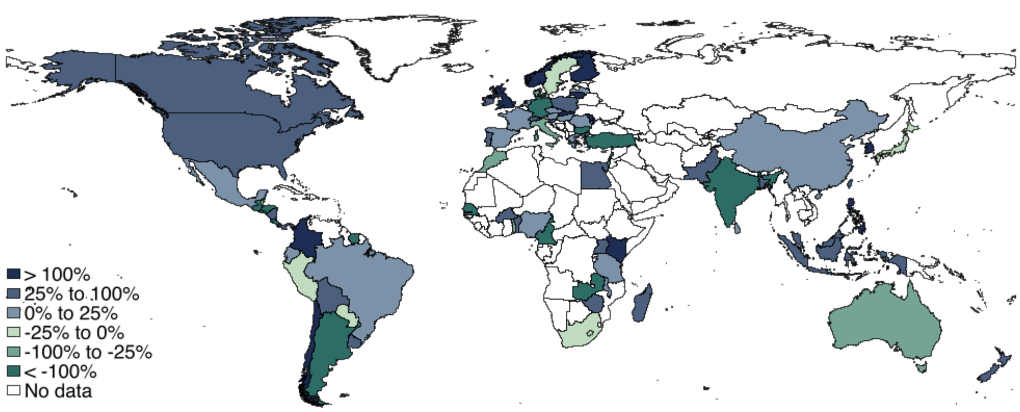
(a) Domestic Prices



(b) Consumer Surplus

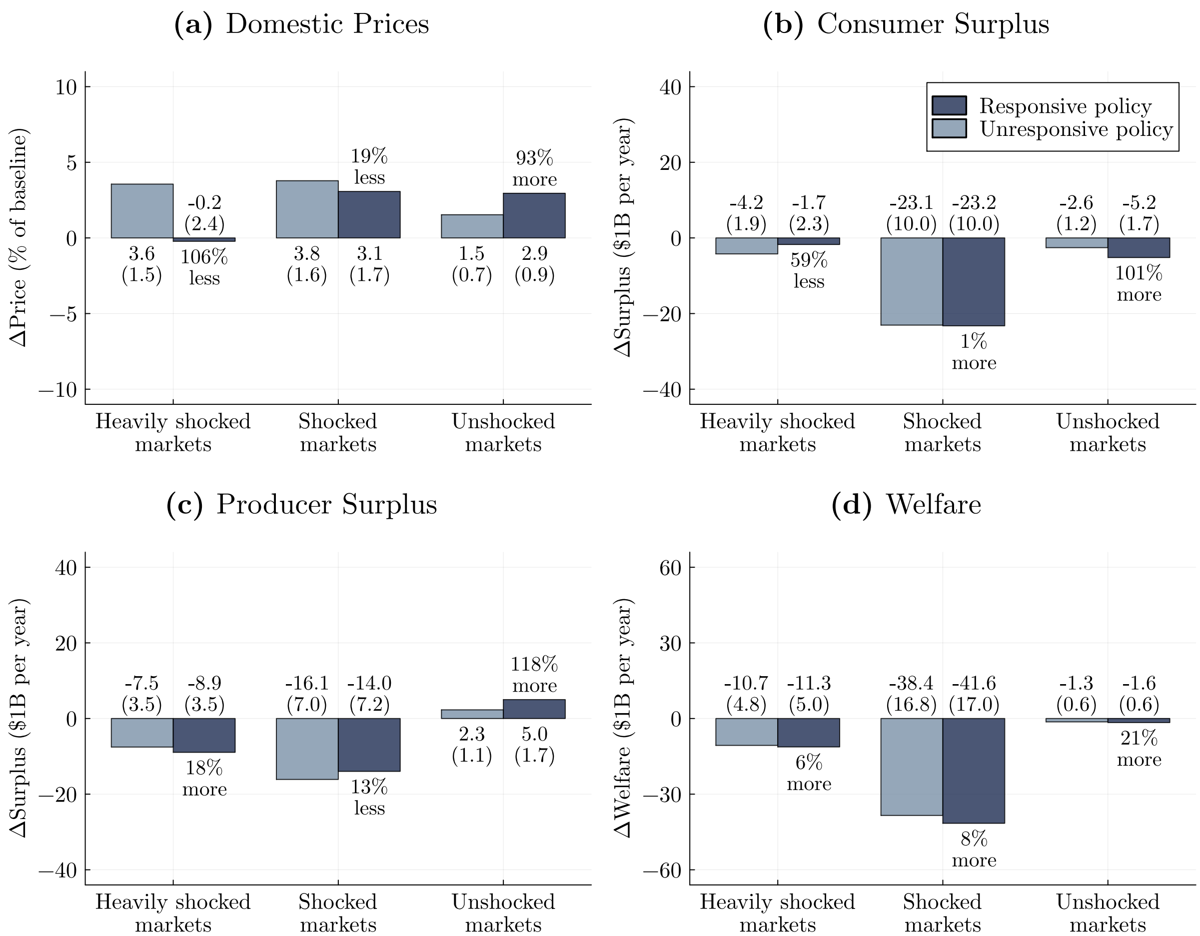


(c) Producer Surplus



We map shock-induced changes in welfare under responsive policy, reported as a percentage difference relative to shock-induced changes in welfare under unresponsive policy. We aggregate to the country level by summing welfare across crops and years. Shocks are observed extreme heat shocks from 1991 to 2019.

Figure A.10: Effects of Responsive Policy in Climate-Change Scenario



We compute shock-induced changes under responsive and unresponsive policy. Shocks are projected extreme heat shocks from GFDL-ESM4 for 2091 to 2100. Responsive policy adjusts as estimated, and unresponsive policy is fixed at baseline levels. We aggregate over countries, crops, and years as follows. For domestic prices, we compute Stone price indices, which weight by expenditure shares, and we report percentage changes relative to baseline prices. For consumer surplus, producer surplus, and welfare, we compute sums and report changes in billions of dollars per year relative to baseline levels. Dollars are inflation-adjusted, year-2020 USD. We report effects separately for heavily shocked markets, which experience a two- or three-quartile change in domestic extreme heat exposure (16% of markets), for shocked markets, which experience a one-quartile change (63% of markets), and for unshocked markets, which experience no change (20% of markets). We report standard errors in parentheses.

Table A.1: Effects of Extreme Heat on Policy, Sensitivity

	(1)	(2)	(3)	(4)
	Dependent Variable is NRA			
	Full Sample	Major Crops	Staple Crops	Cash Crops
Panel A: Excluding 1980s				
Q4 Extreme Heat (Domestic)	-0.059	-0.244	-0.243	0.004
	(0.033)	(0.089)	(0.095)	(0.021)
R-Squared	0.826	0.836	0.861	0.836
Observations	11382	5319	4118	1580
Panel B: Excluding 1990s				
Q4 Extreme Heat (Domestic)	-0.052	-0.268	-0.343	0.006
	(0.043)	(0.130)	(0.127)	(0.028)
R-Squared	0.778	0.748	0.769	0.872
Observations	10339	4951	3810	1520
Panel C: Excluding 2000s				
Q4 Extreme Heat (Domestic)	-0.088	-0.308	-0.295	-0.001
	(0.044)	(0.136)	(0.160)	(0.025)
R-Squared	0.816	0.767	0.783	0.867
Observations	10287	4734	3542	1603
Panel D: Extending to 2019 using Ag-Incentives Data				
Q4 Extreme Heat (Domestic)	-0.051	-0.236	-0.258	0.002
	(0.030)	(0.098)	(0.111)	(0.020)
R-Squared	0.780	0.741	0.768	0.809
Observations	20752	9944	7399	3043
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes

This table reports the relationship between extreme heat exposure and the nominal rate of assistance under different sample selections (cf. the baseline estimates on the largest possible sample in Figure 4). The model is Equation 3.1 and the unit of observation is a country-crop-year. The outcome in all specifications is NRA and the sample of crop used in each column is noted at the top of the column. Each panel focuses on a separate time period. In Panel A, the 1980s are excluded from the sample; in Panel B, the 1990s are excluded from the sample; in Panel C, the 2000s are excluded from the sample; and in Panel C, the sample is extended to 2019 using the Ag-Incentives Database, an unofficial continuation of the World Bank's Distortions to Agricultural Incentives project. All two-way fixed effects are included in all specifications. Standard errors are clustered by market.

Table A.2: Country-Level Effects of Extreme Heat on Policy

	(1)	(2)	(3)	(4)	(5)
	Dependent variable is				
	NRA Total	NRA Output	NRA Border	NRA Domestic	NRA Input
Panel A: Contemporaneous Effects					
Q4 Extreme Heat	-0.155	-0.157	-0.178	0.021	0.004
	(0.078)	(0.078)	(0.075)	(0.029)	(0.002)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.756	0.756	0.730	0.193	0.499
Observations	1864	1864	1864	1864	1864
Panel B: Contemporaneous and Lagged Effects					
Q4 Extreme Heat	-0.124	-0.126	-0.157	0.031	0.004
	(0.083)	(0.083)	(0.078)	(0.042)	(0.002)
Q4 Extreme Heat (Lagged)	-0.274	-0.269	-0.263	-0.006	0.002
	(0.087)	(0.087)	(0.087)	(0.016)	(0.002)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.763	0.763	0.742	0.196	0.507
Observations	1806	1806	1806	1806	1806

This table reports the country-by-year-level relationship between extreme heat exposure and the nominal rate of assistance. The unit of observation is a country-year and the baseline estimating equation is

$$\text{NRA}_{\ell t} = g(\text{ExtremeHeat}_{\ell t}) + \gamma_\ell + \delta_t + \varepsilon_{\ell t}$$

where NRA and extreme heat exposure are aggregated to the country-year level by taking the sum across all major crops, where each crop is weighted by its calorie-weighted share of output during the pre-analysis period. The nonparametric function g is parametrized by indicators for quartiles, where the first quartile is the excluded category; in all specifications, we report only the coefficient on the fourth quartile for concision. Country and year fixed effects are included in all specifications. In Panel A, we only include the contemporaneous value of the quartile shocks. In Panel B, we also include the first lag of all shocks: $g(\text{ExtremeHeat}_{\ell,t-1})$. Standard errors are clustered by country.

Table A.3: Effects of Extreme Heat on Policy With Fewer Fixed Effects

	(1)	(2)	(3)	(4)
	Dependent variable is NRA			
Q2 Extreme Heat (Domestic)	-0.121	-0.167	-0.138	-0.072
	(0.086)	(0.081)	(0.082)	(0.031)
Q3 Extreme Heat (Domestic)	-0.165	-0.255	-0.255	-0.100
	(0.090)	(0.111)	(0.140)	(0.043)
Q4 Extreme Heat (Domestic)	-0.180	-0.416	-0.310	-0.287
	(0.092)	(0.129)	(0.176)	(0.110)
Country-Year Fixed Effects	No	No	Yes	Yes
Crop-Year Fixed Effects	No	Yes	Yes	Yes
Country-Crop Fixed Effects	No	No	No	Yes
R-Squared	0.009	0.102	0.486	0.772
Observations	7699	7698	7439	7439

This table reports the relationship between extreme heat exposure and the nominal rate of assistance in models with fewer fixed effects (cf. the baseline estimates in Figure 4, based on estimating Equation 3.1 with all two-way fixed effects). The unit of observation is a country-crop-year and the outcome variable in all specifications is the nominal rate of assistance (NRA). The regression model in each column includes a different set of two-way fixed effects. In column 1, no fixed effects are included and in the remaining columns, sets of two-way fixed effects are added one-by-one (as noted at the bottom of each column). Standard errors are clustered by market.

Table A.4: Effects of Foreign Extreme Heat By Domestic Extreme Heat Exposure

	(1)	(2)	(3)
	Dependent Variable is NRA		
	Full Sample	Markets with Q3/Q4 Shock	Markets with Q4 Shock
Q2 Extreme Heat (Domestic)	-0.029	-0.057	-0.055
	(0.021)	(0.051)	(0.059)
Q3 Extreme Heat (Domestic)	-0.044	-0.058	-0.083
	(0.026)	(0.050)	(0.062)
Q4 Extreme Heat (Domestic)	-0.136	-0.127	-0.186
	(0.056)	(0.075)	(0.100)
Q2 Extreme Heat (Foreign)	0.031	0.019	0.080
	(0.020)	(0.038)	(0.059)
Q3 Extreme Heat (Foreign)	0.060	0.041	0.078
	(0.027)	(0.045)	(0.076)
Q4 Extreme Heat (Foreign)	0.084	0.080	0.135
	(0.031)	(0.046)	(0.083)
Country-Year Fixed Effects	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes
R-Squared	0.832	0.837	0.903
Observations	11390	6958	2297

This table reports the relationship between the nominal rate of assistance and domestic and foreign extreme heat exposure under different sample selections (cf. the baseline estimates on the largest possible sample in Table 2). The unit of observation is a country-crop-year and the outcome in all specifications is NRA. Domestic extreme heat quartile shocks and the trade-weighted version of the foreign extreme heat quartile shocks are included in all specifications. Columns 2 and 3 restrict the sample to markets that experience domestic extreme heat shocks during our sample period, including markets that experience at least one third or fourth quartile shock (column 2) or markets that experience at least one fourth quartile shock (column 3). All two-way fixed effects are included in each specification and standard errors are clustered by market.

Table A.5: Effects of Import-Weighted and Export-Weighted Foreign Extreme Heat

	(1)	(2)	(3)	(4)
	Full Sample	Net Importer	Full Sample	Net Exporter
Q2 Extreme Heat (Domestic)	-0.026	-0.050	-0.035	-0.021
	(0.022)	(0.040)	(0.021)	(0.018)
Q3 Extreme Heat (Domestic)	-0.044	-0.058	-0.043	-0.043
	(0.027)	(0.045)	(0.026)	(0.026)
Q4 Extreme Heat (Domestic)	-0.135	-0.211	-0.125	-0.126
	(0.063)	(0.149)	(0.056)	(0.043)
Q2 Foreign Extreme Heat (import-weighted)	0.008	0.039		
	(0.020)	(0.033)		
Q3 Foreign Extreme Heat (import-weighted)	0.022	0.055		
	(0.027)	(0.049)		
Q4 Foreign Extreme Heat (import-weighted)	0.065	0.093		
	(0.029)	(0.049)		
Q2 Foreign Extreme Heat (export-weighted)			0.039	0.026
			(0.020)	(0.036)
Q3 Foreign Extreme Heat (export-weighted)			0.073	0.072
			(0.027)	(0.039)
Q4 Foreign Extreme Heat (export-weighted)			0.026	0.103
			(0.046)	(0.042)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.834	0.825	0.839	0.830
Observations	10722	5382	10832	5294

This table reports the relationship between both import-weighted and export-weighted foreign extreme heat exposure and NRA. The unit of observation is a country-crop-year. In columns 1-2, domestic and import-weighted foreign extreme heat shocks are included on the right hand side of the regression. In columns 3-4, domestic and export-weighted foreign extreme heat shocks are included on the right hand side of the regression. Columns 1 and 3 include the full sample while columns 2 and 4 restrict attention to net importing and net exporting markets respectively. All possible two-way fixed effects are included in all regressions. Standard errors are clustered by market.

Table A.6: Effects of International Price Shocks on Policy

	(1)	(2)	(3)
	Dependent variable is		
	NRA	log Price	NRA
Log International Price (Leave One Out)	0.078		0.648
	(0.046)		(0.205)
Q2 Extreme Heat (Domestic)	-0.043		-0.113
	(0.027)		(0.032)
Q3 Extreme Heat (Domestic)	-0.096		-0.216
	(0.036)		(0.055)
Q4 Extreme Heat (Domestic)	-0.098		-0.323
	(0.050)		(0.080)
Q2 Extreme Heat (Foreign)		0.089	
		(0.017)	
Q3 Extreme Heat (Foreign)		0.175	
		(0.026)	
Q4 Extreme Heat (Foreign)		0.219	
		(0.039)	
Country-Year Fixed Effects	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes
R-Squared	0.790	0.934	—
Observations	9124	42984	7095

This table reports the relationship between international price shocks and the nominal rate of assistance. The unit of observation is a country-crop-year. In columns 1 and 3, the estimating equation is

$$\text{NRA}_{\ell kt} = g(\text{ExtremeHeat}_{\ell kt}) + \beta \cdot \log p_{\ell kt}^{I,\text{LOO}} + \gamma_{\ell t} + \mu_{\ell k} + \varepsilon_{\ell kt}$$

where $\log p_{\ell kt}^{I,\text{LOO}}$ is the log of a leave-one-out international average of country-level commodity prices, weighted by agricultural production, and g is spanned by indicators for quartiles (with the first quartile as the omitted category). Column 1 is an ordinary least-squares estimate, and column 3 is an instrumental-variables (IV) estimate using quartiles of foreign extreme heat as instruments. Column 2 shows estimates from the corresponding "first stage" regression, on the largest possible sample. Standard errors are clustered by market.

Table A.7: Policy Effects of Domestic and Foreign Extreme Heat by Election Year

	(1)	(2)	(3)	(4)
	Dependent variable is NRA			
	All Crops	Major	Staple	Cash
Q2 Extreme Heat x No Election	-0.034	-0.052	-0.060	0.032
	(0.029)	(0.042)	(0.048)	(0.077)
Q3 Extreme Heat x No Election	-0.024	-0.069	-0.095	0.066
	(0.038)	(0.066)	(0.073)	(0.103)
Q4 Extreme Heat x No Election	-0.101	-0.134	-0.148	0.099
	(0.060)	(0.099)	(0.104)	(0.137)
Q2 Extreme Heat x Election	-0.018	-0.079	-0.076	0.118
	(0.022)	(0.035)	(0.040)	(0.142)
Q3 Extreme Heat x Election	-0.043	-0.098	-0.097	0.069
	(0.034)	(0.047)	(0.053)	(0.065)
Q4 Extreme Heat x Election	-0.130	-0.320	-0.338	0.144
	(0.072)	(0.138)	(0.150)	(0.145)
Q2 Foreign Extreme Heat x No Election	0.007	0.007	-0.008	-0.042
	(0.031)	(0.041)	(0.040)	(0.072)
Q3 Foreign Extreme Heat x No Election	0.013	-0.002	-0.003	-0.101
	(0.038)	(0.064)	(0.063)	(0.127)
Q4 Foreign Extreme Heat x No Election	0.067	0.083	0.058	-0.073
	(0.045)	(0.086)	(0.081)	(0.107)
Q2 Foreign Extreme Heat x Election	0.050	0.086	0.105	-0.042
	(0.027)	(0.042)	(0.046)	(0.060)
Q3 Foreign Extreme Heat x Election	0.086	0.115	0.133	0.020
	(0.035)	(0.054)	(0.057)	(0.059)
Q4 Foreign Extreme Heat x Election	0.046	0.154	0.171	-0.073
	(0.062)	(0.080)	(0.085)	(0.070)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop-Election Year Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.831	0.791	0.796	0.904
Observations	11380	5881	4994	969

This table reports the relationship between both domestic and foreign extreme heat and the nominal rate of assistance (NRA) during election and non-election years (cf. the baseline analysis with only domestic shocks in Table 4). The unit of observation is a country-crop-year. The model is a variant of Equation 3.5 in which the variables that span g and h are interacted with *Election*, an indicator that equals one in the year before or year during an election, and its complement *No Election*. The variables *Election* and *No Election* vary at the country-by-time level and are therefore absorbed in the corresponding fixed effect. The sample used in each specification is noted at the top of each column. Standard errors are clustered by market.

Table A.8: Policy Effects of Extreme Heat by Central Government Debt

	(1)	(2)	(3)	(4)
	Dependent variable is NRA			
	Full Sample	Major Crops	Major Crops	Major Crops
Q2 Extreme Heat	-0.040	-0.077	-0.151	-0.092
	(0.036)	(0.063)	(0.083)	(0.069)
Q3 Extreme Heat	-0.062	-0.122	-0.323	-0.142
	(0.049)	(0.086)	(0.157)	(0.089)
Q4 Extreme Heat	-0.163	-0.399	-0.614	-0.434
	(0.065)	(0.147)	(0.224)	(0.149)
Q2 Extreme Heat x Central Govt Debt	0.037	-0.005	0.078	-0.007
	(0.062)	(0.101)	(0.122)	(0.125)
Q3 Extreme Heat x Central Govt Debt	0.110	0.065	0.314	0.065
	(0.087)	(0.142)	(0.213)	(0.145)
Q4 Extreme Heat x Central Govt Debt	0.261	0.327	0.675	0.370
	(0.101)	(0.134)	(0.325)	(0.155)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects x Central Govt Debt	No	No	Yes	No
Interactions with change in debt	No	No	No	Yes
R-Squared	0.815	0.790	0.758	0.798
Observations	13544	6260	6260	6020

This table reports the relationship between both domestic and foreign extreme heat and the nominal rate of assistance (NRA) as a function of debt pressure. The model is a variant of Equation 3.1 in which the variables that span g (quartiles of Extreme Exposure, with the first quartile omitted) are interacted with the debt-to-GDP ratio, measured from International Monetary Fund data. The sample used in each specification is noted at the top of each column. All two-way fixed effects are included in each specification. In column 3, we add interactions of country-crop fixed effects with the deb-to-GDP ratio. In column 4, we add interactions between quartiles of extreme heat exposure and the first difference of the debt-to-GDP ratio. Standard errors are clustered by market.

Table A.9: Effects by Distributional Impacts

	(1)	(2)	(3)	(4)
	Dependent variable is NRA			
Income Group (K) is	Top Quarter	Top Half	Bot Half	Bot Quarter
Panel A: Percent of Crop Consumption by Income Group				
Q2 Extreme Heat x Pct Consumed by K	0.034	0.040	-0.035	-0.044
	(0.087)	(0.071)	(0.072)	(0.072)
Q3 Extreme Heat x Pct Consumed by K	0.207	0.174	-0.180	-0.196
	(0.105)	(0.088)	(0.089)	(0.103)
Q4 Extreme Heat x Pct Consumed by K	0.108	0.093	-0.101	-0.128
	(0.134)	(0.123)	(0.125)	(0.140)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.632	0.632	0.635	0.635
Observations	1887	1887	1861	1861
Panel B: Percent of Crop Income Generated by Income Group				
Q2 Extreme Heat x Pct Produced by K	0.081	0.025	-0.028	0.068
	(0.129)	(0.141)	(0.153)	(0.163)
Q3 Extreme Heat x Pct Produced by K	0.114	0.121	-0.131	-0.166
	(0.153)	(0.169)	(0.184)	(0.233)
Q4 Extreme Heat x Pct Produced by K	-0.001	-0.052	0.057	0.116
	(0.184)	(0.201)	(0.218)	(0.290)
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Crop-Year Fixed Effects	Yes	Yes	Yes	Yes
Country-Crop Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.637	0.648	0.648	0.653
Observations	1889	1913	1913	1882

This table reports how the relationship between extreme heat exposure and the nominal rate of assistance is mediated by distributional incidence. The unit of observation is a country-crop-year and the outcome in all specifications is NRA. The model is a variant of Equation 3.1 in which the variables that span g (quartiles of Extreme Exposure, with the first quartile omitted) are interacted with variables that measure the percent (by value) of a crop that is produced or consumed by a given income group in that country, as measured by the World Bank's Household Impacts of Tariffs database. In all cases, we report only the interaction coefficients for concision. In Panel A, we measure consumption shares and, in panel B, we measure production shares. Columns 1-4 vary the group in which we measure consumption or production shares. All two-way fixed effects are included in each specification. Standard errors are clustered by market.

Table A.10: Observed Extreme Heat Exposure

(a) Domestic Shocks

	Observed exposure			
Baseline	Q1	Q2	Q3	Q4
Q1	2,615	1,823	26	0
Q2	0	1,666	1,421	10
Q3	0	0	1,633	570
Q4	0	0	0	1,408

(b) Foreign Shocks

	Observed exposure			
Baseline	Q1	Q2	Q3	Q4
Q1	2,261	1,280	21	0
Q2	0	1,742	1,082	37
Q3	0	0	1,140	1,008
Q4	0	0	0	2,601

(c) Policy Distortions

	Markets		
	All	Shocked	Unshocked
Average observed distortion (|NRA| as %)	33.84	32.81	34.58
Baseline distortion			
Increases under responsive policy (% share)	18.95	29.02	11.69
Unchanged under responsive policy (% share)	45.99	0.61	78.74
Decreases under responsive policy (% share)	35.06	70.37	9.57
Observations	11,172	3,850	7,322

Panel A tabulates baseline and observed domestic extreme heat exposure by quartile. Observed exposure is as observed from 1991 to 2019. Shocks are given by differences between baseline and observed exposure. Observations are country-crop-years. Panel B similarly tabulates foreign exposure. Panel C shows the average magnitude of observed NRA, which captures policy distortions, as well as the expenditure-weighted shares of country-crop-year markets that, relative to baseline, experience increased, unchanged, and decreased policy distortions under responsive policy. We report effects separately for shocked markets, which experience domestic extreme heat shocks, and for unshocked markets, which do not.

Table A.11: Projected Extreme Heat Exposure

(a) Domestic Shocks

	Projected exposure			
Baseline	Q1	Q2	Q3	Q4
Q1	836	2,396	1,164	68
Q2	0	67	2,284	746
Q3	0	0	124	2,079
Q4	0	0	0	1,408

(b) Foreign Shocks

	Projected exposure			
Baseline	Q1	Q2	Q3	Q4
Q1	543	1,863	1,112	44
Q2	0	291	1,843	727
Q3	0	0	230	1,918
Q4	0	0	0	2,601

(c) Policy Distortions

	Markets			
	All	Heavily shocked	Shocked	Unshocked
Average observed distortion (|NRA| as %)	33.84	30.66	34.00	35.13
Baseline distortion				
Increases under responsive policy (% share)	41.32	46.89	45.54	21.88
Unchanged under responsive policy (% share)	14.82	0.00	1.39	75.07
Decreases under responsive policy (% share)	43.86	53.11	53.08	3.05
Observations	11,172	1,978	6,759	2,435

Panel A tabulates baseline and projected domestic extreme heat exposure by quartile. Projected exposure is as projected by GFDL-ESM4 for 2091 to 2100. Shocks are given by differences between baseline and projected exposure. Observations are country-crop-years. Panel B similarly tabulates foreign exposure. Panel C shows the average magnitude of observed NRA, which captures policy distortions, as well as the expenditure-weighted shares of country-crop-year markets that, relative to baseline, experience increased, unchanged, and decreased policy distortions under responsive policy. We report effects separately for heavily shocked markets, which experience a two- or three-quartile change in domestic extreme heat exposure, for shocked markets, which experience a one-quartile change, and for unshocked markets, which experience no change.

Table A.12: Welfare Impacts by Policy Response ($1B per year)

	Markets		
	All	Shocked	Unshocked
Unresponsive policy	-27.22	-25.48	-1.75
Responsive policy	-27.44	-25.51	-1.93
Domestic responses	-26.98	-25.42	-1.56
Foreign responses	-27.99	-25.96	-2.03
Shocked responses	-27.24	-25.47	-1.77
Unshocked responses	-27.37	-25.49	-1.88

The top panel computes shock-induced changes in welfare under responsive and unresponsive policy. Shocks are observed extreme heat shocks from 1991 to 2019. Dollars are inflation-adjusted, year-2020 USD. Responsive policy adjusts as estimated, and unresponsive policy is fixed at baseline levels. The second panel is a decomposition that allows policy responses to domestic shocks but not foreign shocks, then to foreign shocks but not domestic shocks. The third panel is another decomposition that allows policy responses in shocked markets but not unshocked markets, then in unshocked markets but not shocked markets. We aggregate by summing welfare across countries, crops, and years. We report effects separately for shocked markets (34% of markets), which experience domestic extreme heat shocks, and for unshocked markets, which do not (66% of markets).