Food Policy in a Warming World

Allan Hsiao[*] Princeton University
Jacob Moscona[†] Harvard University
Karthik A. Sastry[‡] Princeton University

March 21, 2024

Abstract

Do governments systematically intervene in agricultural markets in response to climate shocks? If so, how do these policy responses affect the aggregate and distributional consequences of climate extremes? To study these questions empirically, we construct a global dataset of agricultural market intervention and extreme heat exposure by country and crop since 1980. We find that extreme heat shocks to domestic production lead to increased consumer assistance. This effect is persistent, primarily implemented via border policies, and stronger in election years when politicians may be particularly responsive to constituent demands. Extreme heat shocks to import partners lead to increased producer assistance, consistent with a mechanism focused on redistribution rather than a direct preference for price stabilization. Combining the estimates with a model, we show that endogenous trade policy can drastically alter the level and distribution of climate damages, both in-sample and for projected climate change.

[*]Princeton University, Department of Economics. Email: ajhsiao@princeton.edu.
[†]Harvard University, Department of Economics. Email: moscona@fas.harvard.edu.
[‡]Princeton University, Department of Economics. Email: ksastry@princeton.edu.

We are especially grateful to Kym Anderson for extremely helpful discussions. We also thank Daron Acemoglu, Rob Elliot, Ishan Nath (discussant), Vincent Pons, Richard Rogerson, and seminar participants at Princeton University, the University of Birmingham, the London School of Economics, the 2023 NBER Fall Conference on Distributional Impacts of Climate Change on the Agricultural Sector, the Fall 2023 Coase Project Conference, and the 2024 ASSA Meetings for helpful comments. Luong Nguyen provided exceptional research assistance.

1 Introduction

In March 2022 a heat wave in India's breadbasket region reduced the country's wheat production by 100 million metric tons, or 11% of expected output (Beillard and Singh, 2022). On May 13, citing concerns that elevated prices threatened food security, India's government announced a ban of wheat exports. While this policy change had potential benefits for Indian consumers, it was highly controversial both in India and around the world. Farmer Ranbeer Singh Sirsa, quoted in the May 14th *New York Times*, 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 Television, 2022). Other critics focused on the global repercussions: on announcement of the policy, global wheat prices jumped a further 6%, exacerbating food security concerns in other countries (Lockett and Fildes, 2022). Moreover, 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 we might expect to recur in an increasingly extreme climate. First, extreme heat will disrupt agricultural production in large parts of the world. Second, governments may not be passive: they can react with policies that balance different stakeholders' interests and shift the burden of climate shocks between consumers and producers. These policy changes will perhaps intensify, or perhaps lessen, the extensive policy distortions that already exist in the agricultural sector (Anderson et al., 2013). Third, these policy choices could mitigate or exacerbate the overall consequences of climate shocks, both domestically and around the world.

In this paper, we study the interaction between climate change and agricultural policy. Does agricultural policy systematically respond to climate extremes, as the examples above suggest? If so, how and why? And what implications does this policy response have for international adaptation to climate change?

To fix ideas about the relevant economic forces, we begin with a model of optimal government policy in an open agricultural economy. A government sets a border tax that distorts the domestic price relative to the international price to maximize a weighted sum of producer surplus, consumer surplus, and government revenue. When the government is utilitarian, tariffs are simple Ramsey (1927) "inverse elasticity" rules that equates marginal revenue and marginal deadweight loss. When the government cares about redistribution, it further manipulates prices to favor producers or consumers at the expense of the other group.

We next study how trade policy responds to climate shocks that restrict domestic supply. We derive a condition on welfare weights and primitive elasticities that delineates whether the government is *constituent focused* or *revenue focused*, and we show that this determines whether the government responds to shocks by assisting consumers or producers. A constituent-focused government places higher weight on producer and consumer surplus relative to government revenue. Their primary 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. Therefore, they respond to the shock with pro-consumer policy changes. This enables consumer adaptation to the climate shock at the cost of intensifying the negative effect on producers. For a revenue-focused government, the dominant concern is that a domestic supply shortage is the most expensive time to subsidize imports (or the least profitable time to tax exports). Therefore, they respond to the shock with pro-producer policy, dampening farmers' economic exposure to shocks while intensifying consumers'. In further results, we discuss how the same considerations shape the government's optimal response to *foreign* climate shocks. We show that these international spillovers could amplify or dampen the effect of domestic policy responses on welfare.

In summary, our model suggests that the relationship between climate shocks and food policy is theoretically ambiguous. The model also highlights that "adaptation through policy" has ambiguous distributional consequences and effects on overall efficiency. The latter depends on how equilibrium policy adjustments interact with existing distortions: climate-induced shifts toward consumer assistance that take the form of dismantling producer subsidies can reduce deadweight loss, while intensifying consumer subsidies can increase it.

To understand how food policy reacts to climate shocks and shapes their economic consequences, it is therefore essential to turn to data. Our empirical strategy is to exploit the differential exposure of country-crop pairs to plausibly exogenous variation in extreme heat over time. We construct a new global data set that measures annual exposure to extreme temperature for every crop-by-country pair since 1980. Our approach combines gridded, global data on daily temperature realizations from the ERA5 dataset (Muñoz-Sabater et al., 2021) with expert-elicited estimates of the maximum growing temperature for individual plant species.[1] Thus, our measure incorporates variation across time, space, and crops.

We measure crop-specific agricultural policy across countries with data from the World Bank's "Distortions to Agricultural Incentives" project (Anderson, 2009, and follow-up work). This database reports the "nominal rate of assistance" (NRA), which measures percent distortions of domestic prices from international prices, for 80 agricultural products and

[1] This approach builds on the measurement strategy developed and validated in Moscona and Sastry (2023) to study the consequences of crop-specific extreme heat in the United States.

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 production or input subsidies. We also use the specific components of the summary NRA measure, as well as independent measures of tariffs from the United Nations' TRAINS (Trade Analysis Information System) database, to identify the specific types of policy that drive our findings. Finally, we measure international production, yields, and trade using the UN FAOSTAT database.

As a prelude to our main analysis, we validate our measure of extreme heat exposure as a negative shock to agricultural productivity. Specifically, we show that top-quartile extreme heat exposure in a given year reduces crop yields by over 20% compared to the bottom quartile in a regression model that absorbs two-way fixed effects at the country-by-year level, country-by-crop level, and crop-by-year level. The fixed effects isolate the differential exposure of different crops *within* a country to temperature trends to identify effects on production and consumption. We will use this precise variation in all subsequent analysis.[2]

Our first main result is that extreme heat exposure substantially reduces nominal rates of assistance. This reduction corresponds to a pro-consumer policy change. We find larger effects when focusing on the most economically important crops, and we show that the results are driven by staple crops rather than cash crops. In particular, for a staple crop, a swing from the first to fourth quartile of extreme heat exposure results in a more than 30 percentage point change in NRA. Concretely, this implies that a country which initially elevates prices 30% above the international price would move to zero, or a country initially with no distortions would move to a 30% domestic consumer subsidy. There is no evidence of pre-existing trends in the relationship between extreme heat and policy, but the effect persists for several years after the extreme heat shock itself. Finally, when we break down the estimated effect across specific policy levers, we find the biggest effects on border policies, including tariffs. Through the lens of our model, these findings are consistent with trade policy driven by constituent focus, especially for economically important staple crops.

Second, we investigate how extreme heat exposure in foreign countries affects agricultural policy. For each country-crop pair, we construct a measure of foreign extreme heat shocks weighted by each country's pre-period import partners. We validate that these foreign shocks predict increases in international prices and study their effects on policy alongside domestic climate shocks. We find that foreign climate shocks lead to more producer-oriented policy. That is, a threat to food security originating overseas has precisely the *opposite* effect as one originating domestically. This finding is consistent with our model of policy choice motivated

[2] This approach contrasts with existing work that is based purely on cross-country variation for individual crops (e.g., Lobell and Field, 2007; Lobell et al., 2011).

by domestic re-distribution, which predicts that domestic and foreign climate shocks have opposite effects on policy because of their asymmetric distributional consequences. A further implication is that, if a heat wave jointly hits many countries that trade with one another, policy responses to foreign shocks partially offset policy responses to domestic shocks. Interestingly, the finding pushes against popular narratives of food policy "contagion" (Ghosal et al., 2023) and "multiplier effects" (de Guzman, 2022) in case studies of climatic, public-health, and geopolitical disruptions of global food trade.

Third, we study long-run, decade-to-decade changes in climate and policy. In principle, short-run responses could differ from long-run responses if there is mean reversion in policy or adaptation via production techniques and trade. Put differently, our finding of significant policy response to short-run "weather fluctuations" need not imply significant policy response to longer-run "climate fluctuations." To study this, we follow the approach of Dell et al. (2012) and Burke and Emerick (2016) and revisit our analysis using longer-run variation. We find that decade-level effects of extreme heat on policy that are consistent with, and slightly larger than, our baseline estimates.

Fourth, we test for evidence of the model's mechanism of constituent versus revenue focus. Our first strategy is motivated by existing work on "political cycles" which hypothesizes that upcoming elections lead governments to place less emphasis on fiscal responsibility.[3] We treat the timing of elections as within-country variation in whether countries are more constituent focused. We find that the effect of extreme heat on policy is almost four times as large in magnitude during the lead up to elections, consistent with our hypothesis and indicative of a strong influence of politics on climate adaptation. Our second strategy treats countries' debt-to-GDP ratio as a proxy for governments' marginal cost of fiscal irresponsibility. The effect of extreme heat on consumer assistance is muted when the debt-to-GDP ratio is high, consistent with the hypothesis that these circumstances induce revenue focus.

In a final section, we combine our model and empirical estimates to quantify how policy responses affect aggregate damages from extreme heat. We first study an in-sample counterfactual in which we remove the responsiveness of policy to extreme heat. Comparing this to the observed scenario, we find that shocked countries use policy to completely shield consumers from possible welfare losses, but at the cost of further harming domestic producers and foreign consumers. Changes in surplus due to responsive policy varies substantially across markets and can be as high as 20 30 percentage points in both directions. The global aggregate effect of responsive policy on welfare varies year-to-year as a function of the geographic distribution of climate shocks. In years when heat waves primarily strike re-

[3]See Nordhaus (1975), Rogoff (1990), Alesina and Roubini (1992), and Akhmedov and Zhuravskaya (2004), as well as Balboni et al. (2021) for a recent application to forest fires in Indonesia.

gions with existing consumer assistance, their effect is to intensify those distortions, increase global deadweight loss, and decrease global welfare. In years when heat waves primarily strike regions with existing producer assistance, their effect is the opposite. In a second counterfactual, we study how endogenous policy mediates the effect of projected end-of-century (2100) climate change. Here, policy responses to climate change exacerbate damages by 14%, since they primarily take the form of further entrenching distortionary consumer assistance. In this way, some countries' efforts to shield consumers from the sharpest effects of climate change comes at the expense of increasing the inefficiency of the global agricultural system.

Our main contribution is to show how agricultural policy responds to climate shocks, shaping their aggregate and distributional effects. We build on existing work studying the causes and consequences of distortions to agricultural incentives. Existing studies have documented these distortions around the world (Krueger et al., 1988; Johnson, 1991; Anderson, 2009) and argued qualitatively that they are driven by politicians' desire to re-distribute between the producers and consumers of food (e.g., Bates, 2014).[4] We depart from existing work by focusing on responses to climate shocks, in the short and long run, rather than political trends or static cross-country differences.[5] An implication of our findings is that climate change may significantly affect the extent of food-policy distortions in the future, possibly fighting against a trend toward further liberalization (Anderson et al., 2013). We also quantify how evolving food policy shapes resilience in the face of climate volatility.

A large literature in environmental economics quantifies the negative impacts of climate shocks on agricultural production (see, e.g., Lobell and Field, 2007; Schlenker and Roberts, 2009; Lobell et al., 2011). Costinot et al. (2016) shows how global adaptation via trade can reduce projected welfare losses from climate change (see also Reilly and Hohmann, 1993; Rosenzweig and Parry, 1994; Randhir and Hertel, 2000). Others study how trade interacts with other adaptation mechanisms including crop switching (Baldos et al., 2019; Hultgren et al., 2022), land and water use (Gouel and Laborde, 2021; Carleton et al., 2022), sectoral reallocation (Rudik et al., 2022; Nath, 2023), and migration and innovation (Cruz and Rossi-Hansberg, 2023). Each takes domestic policy distortions as fixed. We document that policy itself responds to climate shocks, reshaping their domestic and international consequences.

The paper proceeds as follows. Section 2 presents the model. Section 3 introduces our data and measurement strategies. Section 4 presents our main empirical results. Section 5 quantifies the implications of our findings. Section 6 concludes.

[4] Others have studied the link between redistributive goals and/or political favoritism with trade policy (Grossman and Helpman, 1994, 1995; Goldberg and Maggi, 1999; Fajgelbaum et al., 2020; Adão et al., 2023). Baldwin (1989), Rodrik (1995), and Gawande and Krishna (2003) review this literature more broadly.

[5] Bastos et al. (2013) study how rainfall shocks affect agricultural tariffs. Our results are consistent with their finding that country-level rainfall shortages lead to lower agricultural import tariffs.

2 Model

We first describe a simple model of trade policy that motivates our empirical analysis. Our goals are threefold. First, we show that a textbook case with a purely utilitarian objective predicts that trade policy is invariant to domestic productivity shocks. Next, when we allow the government to have a redistribution motive, we show that it is theoretically ambiguous whether policy shifts to assist consumers or producers in response to shocks. Second, we derive a condition which we call the government's *constituent versus revenue focus* that determines which of the two policy responses arises. This will allow us to design a more precise test of the mechanism underlying our main result.

2.1 Set-up

We study the market for a representative agricultural commodity. Consumer demand is $q = Q(p) = Q_0 p^{-\epsilon_d}$, where $Q_0 > 0$ parametrizes the level of demand, p is the price, and ϵ_d is the elasticity of demand. Domestic supply is $y = Y(p, \omega) = Y_0(\omega)p^{\epsilon_s}$, where $\omega \in \mathbb{R}$ represents an adverse productivity shock (e.g., a drought), $Y_0 : \mathbb{R} \to \mathbb{R}_+$ is a decreasing function, and ϵ_s is the elasticity of supply. International net supply, similarly, is $m = M(p, \omega') = M_0(\omega')p^{\epsilon_m}$, where $\omega' \in \mathbb{R}$ is an adverse foreign productivity shock, $M_0 : \mathbb{R} \to \mathbb{R}$ is a decreasing function, and ϵ_m is the elasticity of import supply. We allow either the case of $M_0 > 0$ and $\epsilon_m > 0$, which corresponds to an importing country, or $M_0 < 0$ and $\epsilon_m < 0$, which corresponds to an exporting country. We moreover assume that either $\epsilon_m > \epsilon_s > 1$ or $-\epsilon_m > \epsilon_d > 1$, so foreign supply or demand is more elastic than its domestic counterpart and that all curves are more than unit elastic. The former is a natural assumption if the studied country is small relative to the rest of the world. The latter ensures that the government's revenue from taxation is a concave function of the tax rate. We let $s = m/q \in (-\infty, 1]$ denote the import share of consumption, which is negative in the case of an exporting country.

The government can impose a border tax $\tau \in \mathbb{R}$. The market clears at some domestic equilibrium price $p^* \in \mathbb{R}_+$ if $Q(p^*) = Y(p^*, \omega) + M(p^* - \tau, \omega')$. If $\tau > 0$, then imports are being taxed or exports are being subsidized. If $\tau < 0$, then imports are being subsidized and exports are being taxed. We also let $\alpha = \frac{\tau}{p^* - \tau}$ denote the equivalent *ad valorem* tax. This will correspond to our empirical definition of nominal rate of assistance.

The government sets an optimal border tax $\tau^* \in \mathbb{R}$ to maximize a weighted sum of consumer surplus, producer surplus, and government revenue. That is,

$$\begin{aligned} \tau^* \in \underset{\tau \in (-\infty, p^*)}{\arg\max} & \left\{ \lambda^C \int_{p^*}^{\infty} Q(p)\,\mathrm{d}p + \lambda^P \int_0^{p^*} Y(p,\omega)\,\mathrm{d}p + \lambda^G \tau M(p^* - \tau, \omega') \right\} \\ \text{s.t. } & p^* = P^*(\tau, \omega, \omega') \end{aligned} \tag{2.1}$$

where $\lambda^C, \lambda^P, \lambda^G \in \mathbb{R}_+$ are exogenous parameters specifying the relative weights on each payoff component, and $P^* : \mathbb{R}^3 \to \mathbb{R}_+$ maps policy and fundamentals to the equilibrium price.[6] We make the simplifying assumption that this problem is globally concave in τ.

An important modeling assumption is that the government may place different weights on consumer surplus, producer surplus, and revenue. This is motivated by extensive work studying the political economy of food policy and, in particular, highlighting the importance of redistributive motives (e.g., Bates, 2014). As we will make clear shortly, optimal policy in our model will encapsulate both the desire to redistribute and the desire to manipulate terms of trade.

2.2 What Determines Trade Policy?

We first characterize optimal policy in terms of welfare weights, equilibrium elasticities, and the equilibrium import share:

Proposition 1 (Optimal Trade Policy)**.** *The optimal trade policy satisfies:*

$$\alpha^* = \frac{\tau^*}{p^* - \tau^*} = \frac{1}{\epsilon_m} \left(\frac{\lambda^G\left((1-s)\epsilon_s + \epsilon_d\right) + \epsilon_m \left(\lambda^P(1-s) + \lambda^G s - \lambda^C\right)}{\lambda^G\left((1-s)\epsilon_s + \epsilon_d\right) - \left(\lambda^P(1-s) + \lambda^G s - \lambda^C\right)} \right) \tag{2.2}$$

Proof. See Appendix A.1 □

To obtain intuition for this expression, consider first the utilitarian case in which $\lambda^P = \lambda^C = \lambda^G$. In this case, $\alpha^* = 1/\epsilon_m$. This is an "inverse elasticity rule" or "Ramsey rule," obtained from setting marginal revenue equal to marginal deadweight loss. For an importer, the Ramsey rule implies producer support via an import tax; for an exporter, it implies consumer support via an export tax.

More generally, an additional consideration is the government's desire for redistribution. Marginally increasing the price transfers surplus away from consumers and toward producers and affects tax revenue indirectly through net imports. The extent of this pecuniary transfer

[6] Under our maintained monotonicity, differentiability, and limit-value assumptions on Q, Y, and M, the equilibrium price is unique and the representing function is differentiable and increasing in the first argument.

scales with the price impact of trade policy. That price impact is high when domestic supply and demand are relatively inelastic and when the import share is high.

We next use the result above to describe when the government supports producers or consumers, as a function of primitive welfare weights, import shares, and elasticities:

Corollary 1 (Producer *vs.* Consumer Support)**.** *The government supports producers ($\alpha > 0$) if and only if*

$$\lambda^C < \lambda^P(1-s) + \lambda^G s + \frac{\lambda^G}{\epsilon_m}\left((1-s)\epsilon_s + \epsilon_d\right) \tag{2.3}$$

Proof. See Appendix A.2. □

A high consumer weight pushes the government to subsidize imports or to tax exports. A high producer weight pushes the government to subsidize exports or to tax imports. These predictions follow intuitively from the pecuniary distribution channel described above. Inelastic supply and demand increase the relative importance of the redistribution motive relative to the terms-of-trade manipulation motive, because this increases the government's ability to redistribute via prices. For an importer, decreasing the importance of redistribution pushes away from the import tax that optimally manipulates terms of trade, and therefore toward consumer assistance; for an exporter, the opposite is true.

2.3 How Does Trade Policy Respond to Shocks?

We now study the comparative statics of optimal trade policy. We first define a key condition on government preferences and elasticities of supply and demand that defines whether the government is *constituent-focused* or *revenue-focused*:

Definition 1. *The government is constituent-focused if*

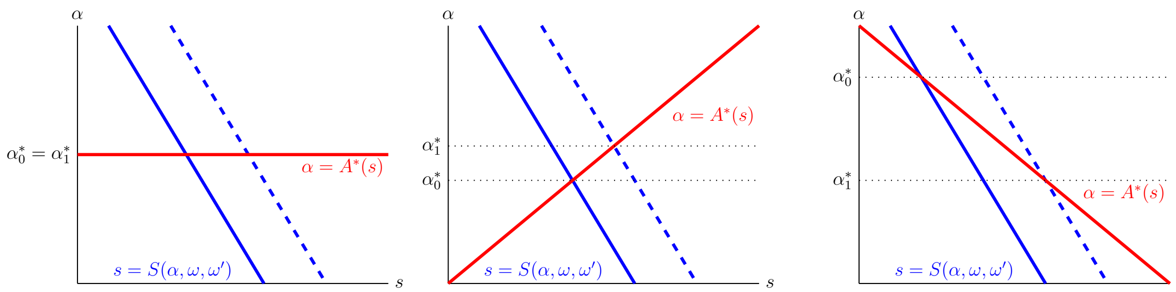
$$\epsilon_s(\lambda^C - \lambda^G) + \epsilon_d(\lambda^P - \lambda^G) > 0 \tag{2.4}$$

The government is revenue-focused if the opposite inequality holds strictly and neutral if the condition holds at equality.

A *constituent-focused* government has relatively high weights λ^C, λ^P on consumers and producers, respectively, and a relatively low weight λ^G on government revenue. Comparing this condition with the comparative statics in Corollary 1, we observe that a constituent-focused government can have pro-consumer or pro-producer policy depending on *which* constituents it values the most. What the condition disciplines, instead, is the relative importance of maximizing domestic welfare versus raising revenue. Finally, we note that the utilitarian government with $\lambda^C = \lambda^P = \lambda^G$ is always *neutral* by this criterion.

Figure 1: Trade Policy and Climate Shocks

(a) Neutral **(b)** Revenue Focused **(c)** Constituent Focused



Notes: Each panel illustrates a case from Proposition 2. The blue lines correspond to the condition $s = S(\alpha, \omega, \omega')$. The dashed line corresponds to a higher value of ω or a lower value of ω'. The red line corresponds to the condition $\alpha = A^*(s)$. We mark the equilibrium values of α^* on the y-axis. The lines are illustrative and do not correspond to a numerical calibration.

We can now show our main result:

Proposition 2 (Trade Policy and Climate Shocks)**.** *The following statements are true:*

1. *If the government is neutral, then α^* is invariant to ω and ω'.*
2. *If the government is revenue-focused, then α^* increases in ω and decreases in ω'.*
3. *If the government is constituent-focused, then α^* decreases in ω and increases in ω'.*

Proof. See Appendix A.3. □

To prove this result, we proceed in two steps. First, we observe that, depending on the parameter case of Proposition 2, the optimal *ad valorem* tariff is a flat (neutral), increasing (revenue focused), or decreasing (constituent focused) function of the import share. The import share, in turn, is a decreasing function of the tariff: producer assistance reduces imports (or increases exports), and consumer assistance does the opposite. The intuition for the final result follows from a graphical argument, visualized in Figure 1. An adverse domestic supply shock (or positive foreign supply shock) increases imports for any level of policy. This has a different effect on optimal policy depending on which of the case.

We now describe the economics behind each case. The neutral government keeps policy completely steady in response to the shock, as observed in the earlier discussion (Panel (a) of Figure 1). Thus, the government takes no action to shield either producers or consumers from the full force of the shock.

The revenue-focused government wants to increase producer assistance when the import share rises. When the import share is higher, the government has a higher marginal incentive to tax imports; when the import share is lower (or export share is higher), the opposite is true. Intuitively, this is true because a domestic supply shortage is the expensive time to subsidize imports or the least profitable time to tax exports, and the revenue-focused government cares especially about these fiscal effects. By supporting producers, the government "stabilizes" the original shock to the import share—that is, the import share goes down less than it would have had the government not reacted (Panel (b) of Figure 1). Since domestic prices are increasing in α, this cushions the blow for domestic producers while hurting domestic consumers. In this sense, a revenue-focused government helps producers adapt to climate change but, in order to do so, must intensify damages for consumers.

The constituent-focused government wants to increase consumer assistance when the import share rises. Higher relative imports shift the benefits of increasing prices toward foreigners, while the costs of increased prices are borne by domestic consumers. This gives the government a marginal incentive to pursue a policy that lowers the domestic equilibrium price—that is, consumer assistance. Note that this logic applies regardless of the initial *level* of policy (or, more fundamentally, its consumer bias). A pro-consumer government with import subsidies would intensify those subsidies because hurting foreign producers is better than hurting domestic ones; a pro-producer government with import taxes would ease those taxes because, after the shock, their (marginal) benefits have shifted from domestic producers to international ones. These policies have an indirect effect on the import share that *amplifies* the direct effect, further inducing imports or curbing exports (Panel (c) of Figure 1). This cushions the blow for domestic consumers while further harming domestic producers. In this sense, a producer-focused government helps consumers adapt to climate change at the expense of intensifying producers' exposure.

Multi-Country Interactions. So far, we have studied a single country setting trade policy in isolation. But our results also shed light on how multiple countries' policy may interact, for instance if they were responding to regional or global warming.

Concretely, consider an extension in which there are additional countries $\ell \in \{1, \dots, L\}$, each with demand function Q_ℓ and supply function Y_ℓ. Each country levies its own distortionary producer assistance τ_ℓ. Markets clear internationally. Thus, equilibrium prices in each "foreign" country, p^*_ℓ, can be written as $p^*_\ell = p^w - \tau_\ell = p^* - \tau - \tau_\ell$, where the second equality defines the world price. Global trade balance requires

$$Q(p^*) - Y(p^*, \omega) = \underbrace{\sum_{\ell=1}^{L} \left(Q_\ell(p^* - \tau - \tau_\ell) - Y_\ell(p^* - \tau - \tau_\ell, \omega_\ell)\right)}_{M(p^* - \tau, (\omega_\ell, \tau_\ell)_{\ell=1}^L)} \tag{2.5}$$

In brackets, we define the imports (or exports) curve from the perspective of the home country. In this translation, producer assistance in any foreign country is tantamount to a positive imports shock. In this way, the results of Proposition 2 can describe a given government's best response to others' policy.

This can be made concrete via a two-country ("home" and "foreign") example. Imagine that the foreign country is a net exporter and it limits exports during a climate emergency. If the home country is revenue focused, then it supports consumers or subsidizes imports. If the home country is constituent focused, then it supports producers or taxes imports.

The model moreover makes predictions for possible *feedback loops* of equilibrium tariff setting. If both home and foreign are revenue-focused, home's consumer support is tantamount to a negative overseas shock for foreign, which pushes foreign toward further consumer support. These interactions *amplify* the initial change to trade policy. If both home and foreign are constituent focused, then home implements producer support and leads foreign to dial back its consumer support. Thus, interactions *dampen* the initial change. Moreover, in the presence of policy feedback loops of either kind, local versus global shocks may propagate very differently. We will return to these ideas in our quantitative analysis (Section 5).

3 Data, Measurement, and Descriptives

3.1 Agricultural Policy

To measure price distortions in agricultural markets, we use data from the World Bank's "Distortions to Agricultural Incentives" project (Anderson and Valenzuela, 2008; Anderson, 2009; Anderson et al., 2013). This data set is an unbalanced panel of information about price distortions for 80 agricultural products and 82 countries from 1955 to 2011. The sample accounts for more than 85% of agricultural production and employment both globally and within each of Africa, Asia, Latin America, and the OECD (Anderson et al., 2013).[7]

The key statistic of interest is the *nominal rate of assistance*. Conceptually, this measures how much higher domestic producer prices are versus prevailing "free market" prices. That is, for crop k in country ℓ at time t,

$$\mathrm{NRA}_{\ell kt} = \frac{P^d_{\ell kt} - P^m_{\ell kt}}{P^m_{\ell kt}} \tag{3.1}$$

where $P^d_{\ell kt}$ is the unit value of production at a distorted price and $P^m_{\ell kt}$ is the unit value of production at an un-distorted market price. This would correspond to our theoretical

[7] In sensitivity analysis, we also use recently collected NRA data from the Ag-Incentives project.

definition of the *ad valorem* tariff α if that were the only policy instrument. In practice, the NRA is computed by measuring the ratio of total assistance paid to producers (in dollars) relative to the total value of production. These sources of assistance include 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). In our empirical analysis, we will use both the summary NRA measure, which captures all forms of policy intervention, as well as the individual components.

The NRA data have two key advantages relative to other measures of trade policy. First, they capture policy instruments other than border taxes. For example, the NRA measure accounts for quantity restrictions, such as the motivating example of an export ban, in terms of the induced price wedge. The NRA measure also accounts for indirect assistance through input price distortions or exchange rate manipulation. This is especially crucial for measuring policies that substitute for 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 see more relevant policy variation and to account for how governments use different instruments as complements or substitutes for one another.

Nonetheless, as an alternative and independent measure of policy, we compile data on crop-specific tariffs from the United Nations' Trade Analysis Information System (TRAINS) database. To do this, we hand-link 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, at the cost of capturing just one relevant dimension of policy.

3.2 Extreme Heat Exposure

To measure agricultural climate shocks, we construct a global dataset of crop-level exposure to extreme heat in each country.

Data Inputs. We measure historical temperatures in the ERA5 database from the European Centre for Medium-Range Weather Forecasts (Muñoz-Sabater et al., 2021). This is a reanalysis data set that 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.

The second are estimates for the global geography of agricultural production 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 maximum potential yield data to construct a 5-by-5 minute grid of the area devoted to each crop circa 2000.

The third are estimates of crop-specific temperature sensitivity 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. This information is used in agronomics and climate science to estimate crop-specific tolerance to climate change (e.g., Hijmans et al., 2001; Ramirez-Villegas et al., 2013; Kim et al., 2018; Hummel et al., 2018), and in our own past work to measure exposure to extreme temperatures (Moscona and Sastry, 2023; Hsiao, 2023).

Measuring Extreme Heat Exposure. Following Moscona and Sastry (2023), we measure crop-specific extreme heat exposure as *the average exposure to extreme temperatures, in degree-days, on land cultivating a given crop.*[8] To define this formally, we partition each country ℓ into grid cells $c \in \ell$ and calculate, for each country, crop, and year:

$$\text{ExtremeExposure}_{\ell kt} = \sum_{c \in \ell} \frac{\text{Area}_{ck}}{\sum_{c' \in \ell} \text{Area}_{c'k}} \cdot \text{DegreeDays}_{ct}(T_k^{max}) \tag{3.2}$$

where $\text{DegreeDays}_{ct}(x)$ 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, and Area_{ck} is the area growing crop k in cell c from the EarthStat data. We average this variable over years and decades in different parts of our analysis.

Our measurement of agricultural climate stress extends existing work constructing global panel data for the exposure of staple crops to average temperature trends (Lobell and Field, 2007; Lobell et al., 2011) and panel data within the United States (Schlenker and Roberts, 2009; Moscona and Sastry, 2023). These data may be of independent interest to researchers interested in studying global trends in climate change and agricultural productivity.

3.3 Additional Data: Production, Trade, Elections, and Debt

We compile data on production, exports, and imports at the crop by country by year level from the United Nations (UN) Food and Agriculture Organization (FAO) FAOStat database. The production data allow us to validate that our constructed climate shocks reduce agricultural yields. The trade data make it possible to identify which countries are net exporters

[8] This strategy builds on prior agronomic work documenting that extreme heat exposure is the quantitatively most important way that temperature affects crop output, including Hodges (1990), Grierson (2001), and especially Schlenker and Roberts (2009). It also builds on the insight that the relevant "cut-off" temperature, above which productivity falls, is very different across crops (e.g. Ritchie and Nesmith, 1991).

(or importers) of each crop, and to construct import shares for each country pair to measure exposure to foreign temperature change.

We also compile data on all election years during our sample period from the latest edition of the Database of Political Institutions (DPI), first introduced by Beck et al. (2001). The database covers elections in 180 countries from 1975-2020 and presents information about election and regime characteristics at the country-year level. Using these data, we code an indicator that equals one during the year of or immediately preceding any national election. Finally, we compile data on government debt from the International Monetary Fund's (IMF) Global Debt Database. We compute central government debt as share of GDP at the country-year level.

3.4 Visualizing the Data

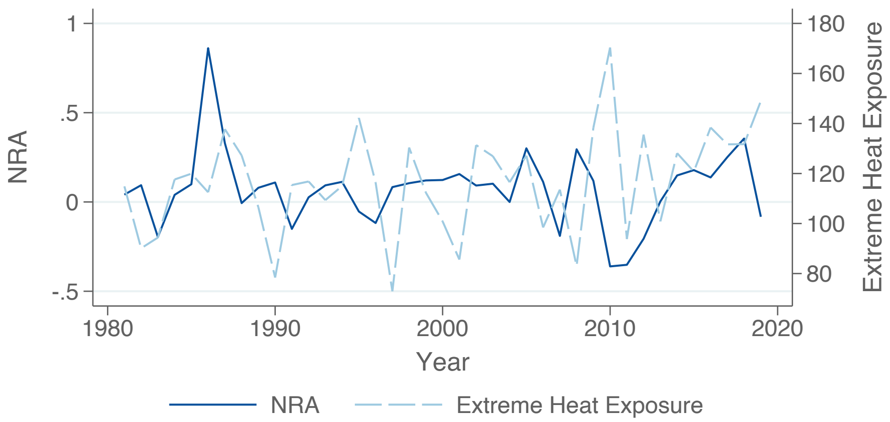
Our data on extreme heat exposure, production and trade cover 166 countries and 126 crops. When merged with our data on agricultural policy, our dataset covers 79 countries and 61 crops. Here, we briefly describe and visualize the variation in our underlying data sources, before turning to the main results.

Figure A.1 presents global maps of average NRA around the world from 2001-2010 for maize, wheat, and rice. There is substantial variation in agricultural policy, both across countries for each crop and within countries across crops. Moreover, several countries have very different policies across crops (e.g., Mexico's policy falls in a different quartile in each map). Figure A.2 shows the *change* in NRA for each country and crop from the 1980s to the 2010s. This also reveals clear differences across crops and countries. Figure A.3 maps changes in $\text{ExtremeExposure}_{\ell k}$ between the 1980s and the 2000s for maize, wheat, and rice. Extreme heat exposure increased in most countries for all three crops. However, for each crop there is substantial variation in the extent of extreme heat exposure growth across countries. There are also large differences within countries and across crops. For example, Brazil is in the third quartile for maize, second quartile for wheat, and fourth quartile for rice. We will exploit this within-country, cross-crop variation in the empirical analysis.

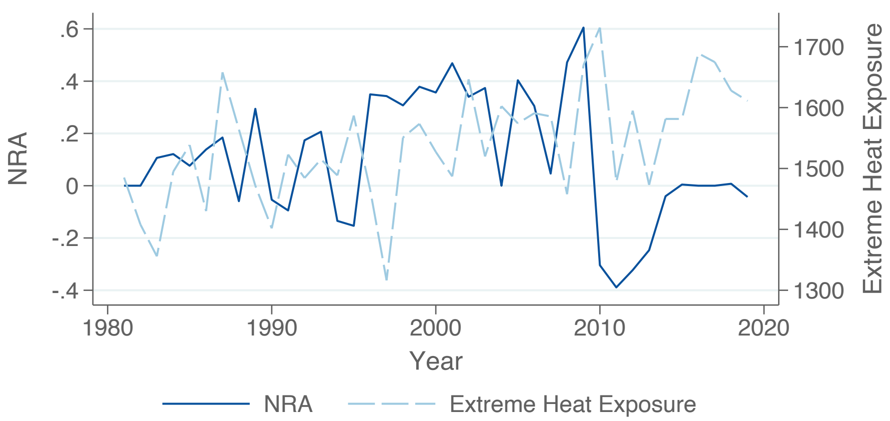
We can also use these raw patterns in policy and climate exposure to anticipate our main analysis and findings. To follow up on our motivating anecdote about Indian policy, we plot the evolution of extreme heat exposure and NRA for Indian maize, wheat, and rice in Figure 2. While extreme heat exposure has increased over time for all three crops, there are also large fluctuations from year to year that we will exploit for identification. Both the level of extreme exposure and the pattern over time are also very different across crops. Visually, increases extreme heat exposure seems to coincide with declines in NRA, and drops

Figure 2: Extreme Heat Exposure vs. NRA Time Series for India: Maize, Rice, and Wheat

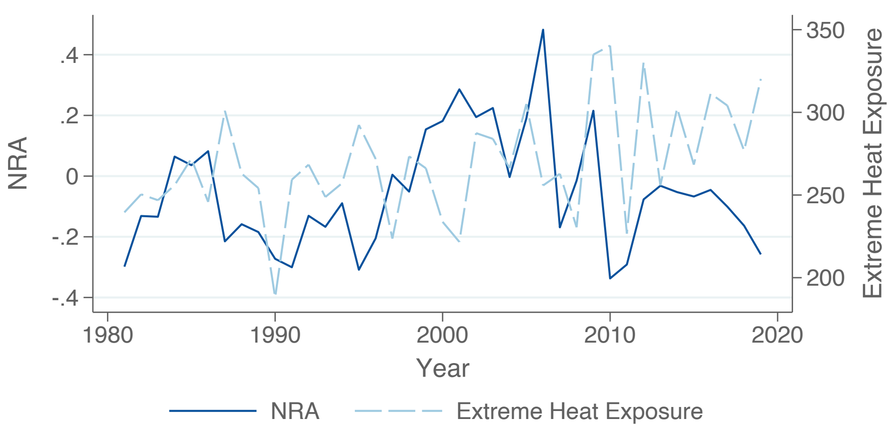
(a) Maize



(b) Wheat

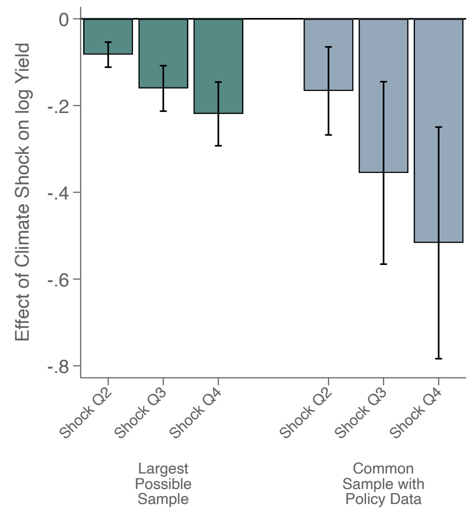


(c) Rice



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

Figure 3: Extreme Heat and Crop Yields



Notes: This figure displays the relationship between quartiles of extreme heat exposure and (log of) crop yields. 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 the estimates from a single regression. The left set of bars is from a regression that includes the full sample for which we can measure the temperature shock and production and the right set of bars is from a regression in which the sample is restricted to the crop-country-year triplets for which we have NRA data. We report 90% confidence intervals.

in extreme heat exposure seems to coincide with increases in NRA. This is a first indication that adverse climate shocks may lead more consumer-friendly policy for staple crops in India. Our main empirical analysis in Section 4 exploits variation across all countries, crops, and years to investigate this pattern systematically.

3.5 Validation: Extreme Heat Exposure Lowers Productivity

Before turning to the main results, we finally document that our measure of extreme heat exposure affects productivity. To this, we estimate the following regression model:

$$\log(\text{yield}_{\ell kt}) = f(\text{ExtremeExposure}_{\ell kt}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \varepsilon_{\ell kt} \tag{3.3}$$

where $\text{yield}_{\ell kt}$ is output-per-area of crop k in country c and year t, and all possible two-way fixed effects are included. $\text{ExtremeExposure}_{\ell kt}$ is defined in Equation 3.2, and we estimate function f that encodes effects by quartile of $\text{ExtremeExposure}_{\ell kt}$. 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 any country-specific or crop-specific trends, or differences in crop specialization across countries.

Estimates of Equation 3.3 are displayed in Figure 3. We find a large, negative effect of extreme heat exposure on yields. Compared to the yields in the bottom extreme heat quartile, yields in the top extreme heat quartile are over 20% lower. When we restrict attention to the subsample of observations for which we also have policy data, our estimates are comparable and slightly larger.[9] Together, these estimates indicate that our measure of extreme heat exposure captures the negative effects of temperature on agricultural productivity.

4 Empirical Results

In this section, we present our four main empirical findings. First, extreme heat shocks to domestic production induce pro-consumer agricultural policies. Second, adverse shocks to import partners have the opposite effect, pushing toward pro-producer policies. Third, these effects are persistent and are amplified when studying low-frequency (decade-by-decade) changes. Fourth, these effects are amplified in scenarios when governments may plausibly care more about helping constituents in the short-term and less about fiscal responsibility, consistent with our proposed model mechanism.

4.1 Local Temperature Extremes Lead to Pro-Consumer Policy

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

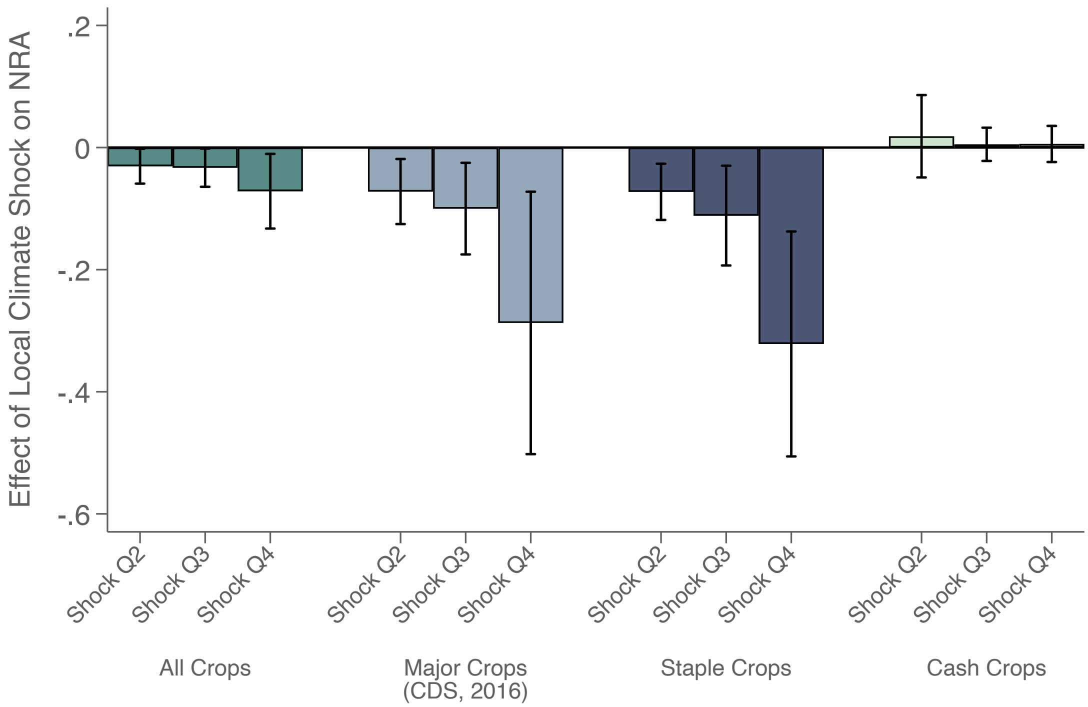
$$\text{NRA}_{\ell kt} = g(\text{ExtremeExposure}_{\ell kt}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \varepsilon_{\ell kt} \tag{4.1}$$

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 indicator functions for each of the four quartiles of $\text{ExtremeExposure}_{\ell kt}$. 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-green bars). Experiencing fourth-quartile (compared to first-quartile) extreme heat exposure reduces NRA by 0.072. This corresponds to a 7.2%

[9] These results are also consistent with the findings of Moscona and Sastry (2023) that Extreme Exposure predicts adverse agricultural outcomes and, moreover, outperforms comparable measures that do not account for crop-specific tolerance in historical panel data from the United States.

Figure 4: Extreme Heat and Agricultural Policy



Notes: This figure displays the relationship between quartiles of extreme heat exposure and NRA. 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. The sample of crops included in each regression is noted below each set of bars. We report 90% confidence intervals.

reduction of domestic prices relative to international prices. In our panel data, this corresponds to 0.092 in-sample standard deviations of the NRA variable. Through the lens of the model, this finding is consistent with a *constituent friendly* government (i.e., case 3 of Proposition 2). The finding is moreover consistent with the motivating stories of the Introduction, including India's 2022 ban on wheat exports following a national drought, as well as the time-series patterns for India visualized in Figure 2. Viewed through this lens, our results confirm that such policy reactions are systematic and quantitatively large relative to the baseline cross-country and cross-crop variation in agricultural policy.

We next focus on the most economically important crops by restricting the sample to the ten crops that are the subject of analysis in Costinot et al. (2016).[10] Our estimates using this sub-sample (blue-grey bars) are substantially larger in magnitude: experiencing high (compared to low) extreme heat exposure reduces NRA by 29 percentage points or 0.37

[10]These crops are bananas, cotton, maize, rice, soybeans, sugar, tomatoes, wheat, potatoes, and palm oil.

in-sample standard deviations. Moreover, the fourth-quartile effect is substantially larger than, and statistically distinguishable from ($p = 0.06$), the third-quartile effect. This finding suggests that most extreme climate shocks may have a disproportionate effect on policy.

Finally, we compare the effect for major staple crops and major cash crops.[11] The third set of bars (dark-blue bars) reports our estimates for staple crops, and the results closely mirror the preceding specification. We find large, negative effects of higher extreme heat exposure on policy and the effect is particularly large for the highest values of extreme heat exposure. Experiencing high (compared to low) extreme heat exposure for staple crops reduces NRA by 32 percentage points or 0.41 standard deviations. Once more, the fourth-quartile effect is statistically distinguishable from the third-quartile effect ($p < 0.01$). In contrast, we find very different effects on cash crops (light green bars). We find no evidence that extreme heat exposure affects agricultural policy for cash crops. The effect for all quartiles is statistically indistinguishable from zero. This suggests that the economic mechanisms underlying the determination of staple-crop and cash-crop policy may be very different. In particular, the finding of zero effect for cash crops would be consistent with the model's "neutral," utilitarian case, in which optimal policy corresponds to the Ramsey rule.

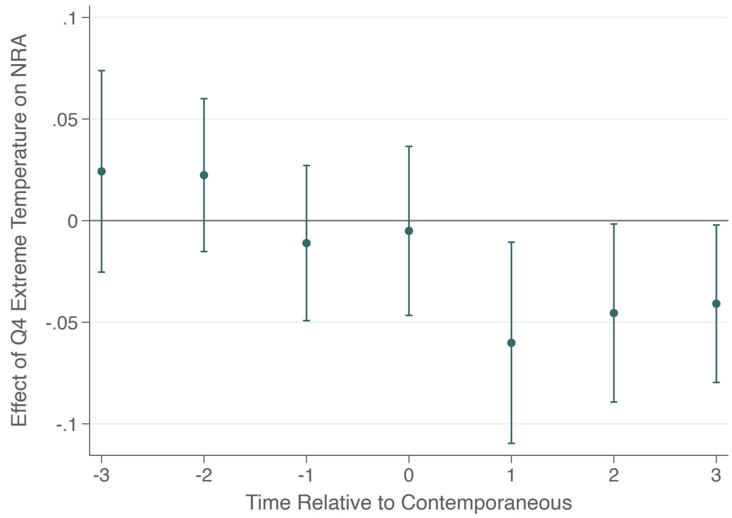
Together, these estimates suggest that exposure to extreme heat reduces NRA, leading to more consumer-oriented agricultural policy. The effects are particularly pronounced for staple crops and for the highest levels of exposure to extreme temperatures.

Dynamics. So far, we have estimated the contemporaneous effect of extreme heat exposure on policy. We next investigate the effect of leading and lagged values of extreme heat exposure. This makes it possible to check if our main estimates are driven by pre-existing trends and to investigate persistence in the effect.

Figure 5 reports estimates of Equation 4.1 focusing only on the top-quartile effect and including three leads and three lags in the regression. Each coefficient can be interpreted as the effect of an extreme temperature shock in that period holding fixed temperature realizations in the contemporaneous period and all other included lags and leads. The first conclusion from the figure is that there is no evidence of pre-existing trends: the coefficient estimates on all the leading values are small in magnitude and statistically indistinguishable from zero. The second conclusion is that the effect of an extreme temperature shock on trade policy seems to persist. The three lagged values suggest that a temperature shock reduces NRA for the subsequent three years, with the largest effect taking place in the year following the shock year.

[11] 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.

Figure 5: Extreme Heat and Agricultural Policy, Dynamics



Notes: This figure displays the relationship between leads and lags of top-quartile extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. All displayed coefficients are estimated from a single regression that includes three leads and three lags of top-quartile exposure, along with the contemporaneous value. Each bar corresponds to an estimate from a separate regression. We report 90% confidence intervals.

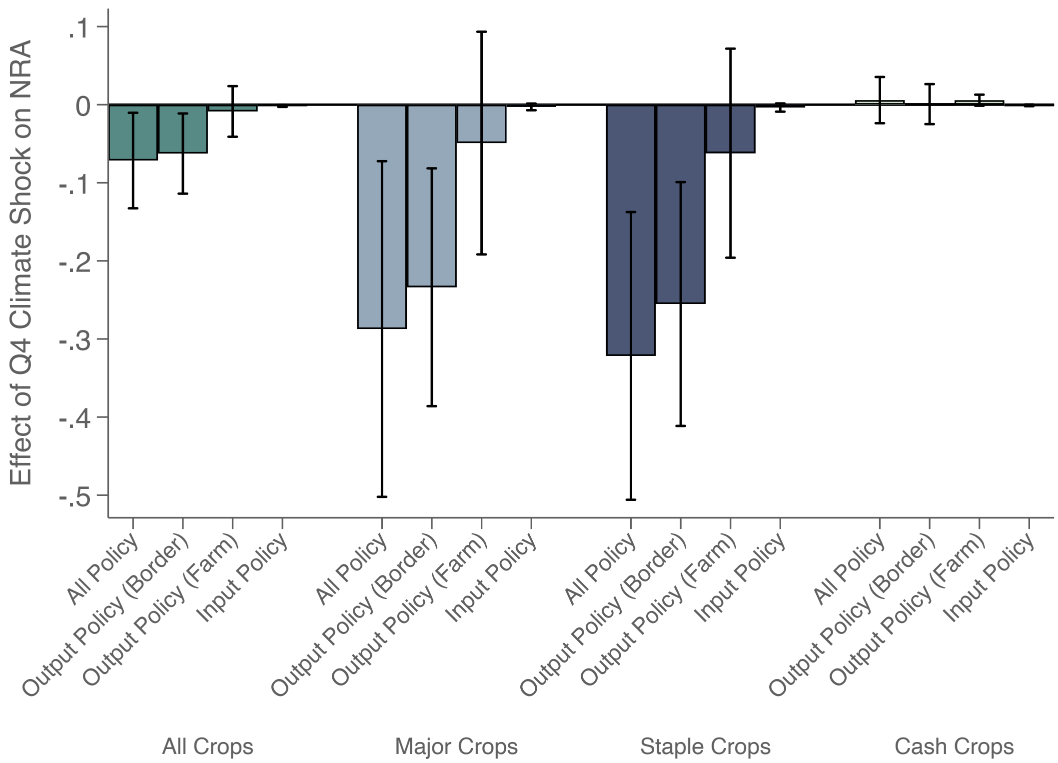
Types of Policy. The results in Figure 4 focus on the summary NRA measure which combines all types of policy. We argued earlier that this is desirable to identify the economically relevant net effect of policy. Nonetheless, it may be interesting to better understand exactly which policies drive our overall findings. For instance, it is possible that our baseline results mask partially offsetting responses of different policies.

To this end, we estimate Equation 4.1 using each component of overall NRA as a separate dependent variable. The estimates are presented in Figure 6. We report the effect of the top quartile of extreme heat exposure; the four sets of bars report the results for the sample of all crops, major crops, staple crops, and cash crops respectively.

Our first observation is that all forms of policy move in the same direction. This helps justify our baseline strategy of bundling together all policies in the baseline NRA measure. If instead we found partially offsetting effects with different signs, we might have concluded that very different economic and political mechanisms underlie each policy choice.

Our second observation is that 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., output price support) and absent for policies that affect agricultural inputs (e.g., fertilizer subsidies). This finding is consistent with our modeling approach.

Figure 6: Extreme Heat and Agricultural Policy by Policy Type



Notes: This figure displays the relationship between top-quartile extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each bar corresponds to an estimate from a separate regression. The outcome in each case is a different component of policy, labelled below the bar. The sample of crops included in each regression is noted below each set of bars. We report 90% confidence intervals.

We also replicate our baseline findings using crop-specific tariffs from the TRAINS database as the dependent variable. These estimates are reported in Figure A.11. High exposure to extreme temperatures leads to reductions in crop-specific tariffs. Consistent with the main results, these findings are driven by staple crops and extreme heat exposure has no effect on tariff policy for cash crops (second and third set of bars). This is consistent with our finding within the NRA data that effects are concentrated within border policies.

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. There are several reasons to focus on the country-crop-year level analysis. First, the country-crop-year level is the unit of analysis at which policy is set and measured and the relevant unit for measuring exposure to damaging climate trends. Second, as illustrated by Figures A.1 and A.3, there is substantial variation in both policy and extreme heat exposure across crops and within countries. Finally, the ability to include country-by-year fixed effects in our baseline specification makes it possible to fully absorb any country-level trends or shocks that might spuriously co-vary with either policy or temperature. This is an especially salient concern for our study, since research has suggested that there are significant trends in NRA (Anderson et al., 2013) and in the climate (due to planetary warming).

Nonetheless, it is also useful to study trends at the country level to investigate how our crop-country-year estimates "add up." These estimates could be larger in absolute value than our baseline estimates if governments are more responsive to high overall exposure to extreme heat, rather than high exposure for a single crop, since this amplifies hardship for consumers. They could be smaller in absolute value if politicians face a political budget that makes it harder to change policy across multiple crops at the same time.

To study this, we average our baseline data to the country-year level, focusing on the ten major crops 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 specification, which is the country-year analog of our baseline specification:

$$\mathrm{NRA}_{\ell t} = g(\mathrm{ExtremeExposure}_{\ell t}) + \gamma_\ell + \delta_t + \varepsilon_{\ell t} \tag{4.2}$$

The estimates are reported in Figure A.5. While the estimates are less precise than our baseline results, they point to a negative relationship between country-level extreme heat exposure and weighted country-level NRA. Consistent with the findings from Figure 6, these estimates are driven by border market policies (second set of bars) and country-level extreme heat shocks have no effect on input market policy (not reported). Moreover, consistent with Figure 5, we estimate slightly larger and more precise effects focusing on the first lag of the extreme heat shocks (third and fourth set of bars). Finally, these estimates are comparable in magnitude to the estimates from the country-crop-year specification (see Figure 4), indicating that cross-crop interactions do not seem to have a quantitatively important effect.

Sensitivity Analysis. We conduct a series of sensitivity checks to probe the robustness of our findings. First, we reproduce our baseline result using all NRA data from 1955-2011 (Figure A.6). In our baseline estimates, we focus on the period 1980-2011 because this is the period during which there is higher-quality global temperature data and more complete policy data; however, the results are very similar if we use the back-filled version of the ERA temperature data. Second, we show that the results are also similar if we extend the sample to more recent years (and to a handful of additional crop-country pairs) using alternative data on nominal rates of assistance from Ag-Incentives (Figure A.7).[12] Third, we show that our baseline results are not driven by temperature extremes or policy regimes during any particular decade in our sample period: the results are very similar if we drop each decade from the analysis (although the standard errors are somewhat larger due to the smaller sample size). These findings are displayed in Figures A.8 to A.10.

4.2 Importer Temperature Extremes Lead to Pro-Producer Policy

The previous section documented that local extreme heat shocks significantly reduce NRA, leading to more consumer-oriented policy. Some anecdotes suggest that this could lead to international cascades: if one country limits exports following an period of extreme heat, so too might other countries, compounding the effect of the initial shock on international trade. Ghosal et al. (2023) refer to this process as the "contagion of food restrictions" and point to examples in which countries restricted exports, allegedly in response to export restrictions enacted by their trading partners.[13] In the model, both this contagion mechanism and the opposite, whereby international interactions *dampen* initial policy responses, are possible. But only the latter would be consistent with our earlier finding that climate shocks induce pro-consumer policy (see Proposition 2).

To systematically investigate how policy reacts to foreign climate shocks in the data, we measure the extreme heat exposure experienced by import partners as

$$\text{ForeignExtremeExposure}_{\ell kt} = \sum_{\ell' \neq \ell} \text{ImportShare}_{\ell' \to \ell k} \cdot \text{ExtremeExposure}_{\ell' kt} \tag{4.3}$$

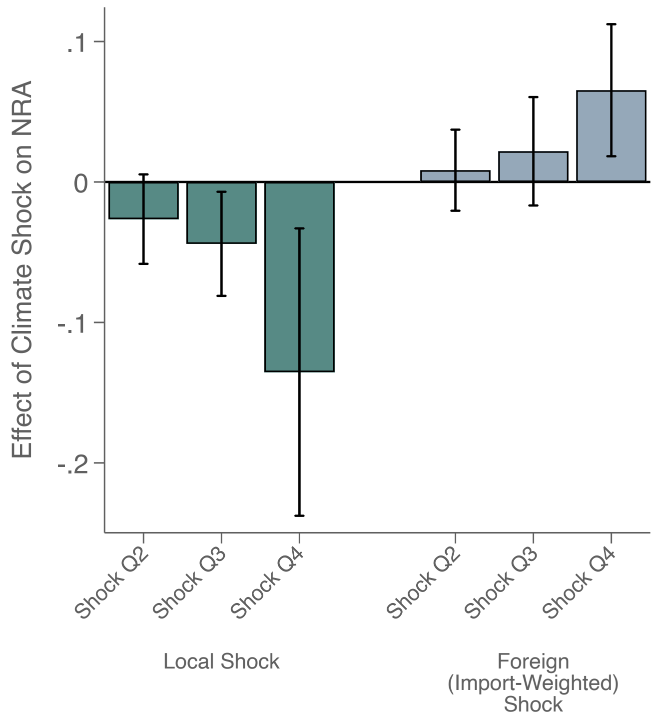
where $\text{ImportShare}_{\ell' \to \ell k}$ is the share of imports of crop k to ℓ from ℓ'. This measure captures the exposure of each country-crop to foreign climate shocks, weighted by import shares. Figure A.4 maps the change in $\text{ForeignExtremeExposure}_{\ell kt}$ from the 1980s to the 2010s for maize, wheat, and rice, revealing substantial variation both across countries and within countries across crops. In Figure A.12, we validate this measure of foreign extreme temperature exposure by showing that it has a large, positive effect on measured crop prices.[14]

[12] We do not treat this as the baseline specification because there are differences in methodology between the two data sets and we do not have access to the raw data to construct one from the other. When we estimate a regression that includes data from both, we include an indicator that equals one if the outcome data came from Ag-Incentives with all the two-way fixed effects in order to capture average differences due to changes in methodology.

[13] For example, they write, "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." (Ghosal et al., 2023).

[14] In particular, we estimate the relationship between the production-weighted global price for each crop (leaving out the importing country ℓ in question) and show that higher values of $\text{ForeignExtremeExposure}_{\ell kt}$

Figure 7: Local vs. Foreign Extreme Heat Shocks



Notes: This figure displays the relationship between quartiles of local and foreign (import-weighted) extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. All bars are estimated from a single regression. The left of bars presents the effect of quartiles of local extreme heat exposure and the right set of bars presents the effect of quartiles of foreign extreme heat exposure. We report 90% confidence intervals.

To investigate the effect of both local and importer temperature extremes on agricultural policy, we estimate an augmented version of Equation 4.1 that includes both the local and the foreign temperature shocks.

$$\text{NRA}_{\ell kt} = g(\text{ExtremeExposure}_{\ell kt}) + h(\text{ForeignExtremeExposure}_{\ell kt}) + \gamma_{\ell t} + \delta_{kt} + \mu_{\ell k} + \varepsilon_{\ell kt} \quad (4.4)$$

Functions g and h capture effects by quartile, and we include all two-way fixed effects.

Estimates of Equation 4.4 are displayed in Figure 7. The left three bars show the effect of each quartile in local extreme exposure. Consistent with the baseline results, we continue to find negative effects of local extreme heat exposure on NRA after also conditioning on foreign extreme heat exposure.[15] The right three bars show the effect of foreign extreme

are associated with higher crop prices, conditional on country-year and country-crop fixed effects.

[15]The estimates are also very similar in magnitude when we instead use the tariff from the TRAINS database as the dependent variable and control for foreign extreme heat exposure (Figure A.11, third through sixth set of bars).

heat exposure. Higher foreign extreme heat exposure is associated with an increase in NRA (i.e., more producer-friendly policy). That is, if food shortages arise due to international rather than domestic shocks, they induce the opposite policy response. These effects are smaller in absolute value than the effect of local extreme heat exposure, suggesting a stronger response to local climate distress. Nevertheless, our estimates are precise enough to rule out negative effects of foreign temperature effects and are inconsistent with the "contagion of food restrictions" view of global food policy.

In our main analysis of foreign exposure, we exploit precise variation in shocks to import partners and estimate a regression model with crop-by-time fixed effects. This approach has the advantage of partialling out other possible global confounds, like global crop demand shocks. A possible disadvantage is that we ignore a large portion of common variation in world prices. To investigate how other sources of world price variation affect agricultural policy, we estimate a variant of Equation 4.4 in which we remove the crop-by-time fixed effect and and replace Foreign Extreme Exposure with (i) a leave-one-out, production-weighted average of global extreme exposure shocks or (ii) a production-weighted average of crop prices (i.e., the "world price"). We show the results in Figure A.13. We find that global climate shocks thusly defined and global price increases lead to producer assistance, confirming our original finding.

As discussed above, the opposite effects of domestic and foreign shocks is consistent with our model, in which domestic and foreign shocks had asymmetric distributional effects from the perspective of the government. These findings are inconsistent with a view of the world in which all food security concerns induce the same policy response, for instance if they arise purely from elevated consumer needs when food is scarce and prices are high.[16]

4.3 Long-Run Effects

So far, we have investigated the relationship between yearly fluctuations in extreme heat exposure and yearly changes in policy. This year-to-year variation is useful because it makes it possible to identify the causal 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 estimates of the effect of long-run changes in the climate on policy (see, e.g., Burke and Emerick, 2016). For example, while policy might respond to short-run fluctuations in the weather, in the long run patterns of trade or production might adapt to the change in climate and limit the effect of warming on policy.

[16]This could be captured in a variation of our model that allowed the elasticity of demand to fall when food consumption is lower.

Table 1: Decade-Level Estimates

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is NRA				
Sample:	Full Sample		Major Crops	Staple Crops	Cash Crops
Years of Extreme Heat (Local)	-0.0242**	-0.0252**	-0.0620**	-0.0758**	-0.0311
	(0.0111)	(0.0110)	(0.0259)	(0.0266)	(0.0400)
Years of Extreme Heat (Foreign Import-Weighted)		0.0179*	0.0254*	0.0237	0.0272
		(0.00969)	(0.0123)	(0.0127)	(0.0185)
Country x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country x Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes
Crop x Decade Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,951	1,951	905	771	215
R-squared	0.905	0.905	0.917	0.919	0.902

Notes: The unit of observation is a country-crop-decade triplet. The dependent variable is the NRA and the sample is listed at the top of each column. Standard errors are double-clustered by country and crop and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

To investigate this, we collapse our data to the decade-level and estimate versions of Equation 4.1 in which the unit of observation is a country-crop-decade triplet. The independent variables of interest are the number of years during the decade with high (fourth-quartile) *local* exposure to extreme heat and the number of years during the decade with high *foreign* exposure to extreme heat. These estimates are reported in Table 1. In the first column, we focus on the full sample of crops and only include local extreme heat exposure. Consistent with the yearly analysis, we estimate a negative and significant effect. Each additional year of extreme heat exposure reduces the decade's average NRA by about 0.04 standard deviations and ten years of extreme heat exposure (which occurs in about 5% of the sample) reduces the decade's average NRA by about 0.4 standard deviations. A full decade of extreme-heat exposure would induce a 24% pro-consumer wedge in domestic prices relative to international prices. This is larger than our year-on-year estimate from Figure 4.

In column 2, we also include foreign extreme heat exposure. We again find that the effect of foreign extreme heat exposure goes in the opposite direction and is (weakly) statistically significant. We can also rule out sizeable negative effects that would be consistent with international policy "contagion." In the next two columns, following our preceding analysis, we restrict attention to the major crops in Costinot et al. (2016) and to staple crops. Consistent with the yearly analysis, we estimate substantially larger effects of local extreme heat exposure on this sample. In the case of the staple crop sample, an additional year of extreme heat exposure reduces NRA by 0.11 standard deviations. Finally, in column 5 we restrict attention to cash crops. As in the yearly analysis, we find no evidence of a relationship between extreme heat exposure and crop-specific policy.

4.4 Mechanisms: Testing for Constituent Focus

All of our results suggest that the "constituent-focused" case from Proposition 2 dominates on average. To investigate this mechanism directly, we use two strategies. The first is to study heterogeneity of effects based on proximity to election years. The second is to study heterogeneity of effects based on countries' fiscal vulnerability.

In our first strategy, we use elections as a positive shock to concerns about constituents relative to fiscal responsibility. A large literature on political cycles has documented that upcoming elections tend to reduce fiscal responsibility and to lead to policies designed to win the support of constituents (e.g. Alesina and Roubini, 1992; Akhmedov and Zhuravskaya, 2004). Therefore, if our proposed mechanism is true, we would expect all of our baseline results to be exacerbated when there is an election and when politicians are more likely to sacrifice fiscal responsibility in order to keep voters content.

To investigate this, we estimate an augmented version of Equation 4.1 that includes interaction terms between extreme heat exposure and (i) indicators for election years and (ii) indicators for non-election years.[17] The findings are presented in Table 2. Across the board, we find evidence of much more extreme effects during elections. As in the main results, this is especially true when we restrict attention to major crops or staple crops (columns 2-3), and we find no effect in either election or non-election years when we focus on cash crops (column 4). In column 2, for example, the effect of a high extreme heat shock is four times as large during an election year, and the difference is significant ($p = 0.03$).

The model also suggested that countries more focused on avoiding revenue loss would respond to climate shocks with *producer* oriented policy. To investigate this side of the policy trade-off, we use each government's accumulated debt-to-GDP ratio as a rough proxy for the government's ability to forego fiscal revenue in order to shield constituents from the climate shock. Table A.1 reports estimates from an augmented version of Equation 4.1 that includes interaction terms between extreme heat exposure and the central government debt-to-GDP ratio in each country-year. The first column includes our full sample of crops and the remaining columns focus only on the set of ten major crops. The negative effect

[17] 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.

Table 2: Extreme Heat and Agricultural Policy Heterogeneity by Election Year

	(1)	(2)	(3)	(4)
	Dependent Variable is NRA			
	Full Sample	Major Crops	Staple Crops	Cash Crops
Q2 Extreme Heat Exposure x No Election	-0.0429*	-0.0724	-0.0509	-0.0259
	(0.0222)	(0.0445)	(0.0390)	(0.0486)
Q3 Extreme Heat Exposure x No Election	-0.0138	-0.0788	-0.0561	-0.0182
	(0.0236)	(0.0654)	(0.0719)	(0.0163)
Q4 Extreme Heat Exposure x No Election	-0.0172	-0.0948	-0.104	-0.0126
	(0.0374)	(0.101)	(0.0946)	(0.0216)
Q2 Extreme Heat Exposure x Election	-0.0120	-0.0689**	-0.0820**	0.0680
	(0.0172)	(0.0315)	(0.0316)	(0.0600)
Q3 Extreme Heat Exposure x Election	-0.0363	-0.110**	-0.145**	0.0217
	(0.0230)	(0.0543)	(0.0627)	(0.0223)
Q4 Extreme Heat Exposure x Election	-0.108**	-0.382**	-0.436***	0.0203
	(0.0490)	(0.149)	(0.142)	(0.0246)
p-value, Q4 x Election - Q4 x No Election	*0.08*	*0.03*	*0.04*	*0.34*
Country x Year Fixed Effects	Yes	Yes	Yes	Yes
Crop x Year Fixed Effects	Yes	Yes	Yes	Yes
Country x Crop x Election Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	15,860	7,432	5,671	2,343
R-squared	0.855	0.851	0.874	0.923

Notes: The unit of observation is a country-crop-year. Election is an indicator that equals one in the year before or year during an election. The sample used in each specification is noted at the top of each column. Standard errors are double clustered by country and crop-year and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

of extreme heat exposure is substantially diminished when central government debt is high, and in two of the four estimates it flips sign (although is not significantly distinguishable from zero). The estimates are qualitatively similar in column 3, when we control flexible for central government debt interacted with country-by-crop fixed effects, and in column 4, when we control for extreme heat exposure interacted with the *change* in government debt, in order to account for year-to-year changes in fiscal policy or incumbent political orientation.

Together, these estimates suggest that the constituent focus of politicians is an important mechanism driving our results. Constituent focus is particularly pronounced during election years, when politicians are appealing for constituent support. They also indicate that the timing of climate shocks *vis-à -vis* political cycles may shape their economic consequences.

5 Counterfactuals: Policy and Climate Adaptation

We now combine our empirical estimates with our model to quantify the effects of endogenous agricultural policy on adaptation to climate shocks, both in-sample and out-of-sample. We have two broad findings. First, responsive policy creates a clear trade-off between domestic consumers and producers, with further spillovers through international prices. Second, the effects on global welfare depend on the interaction of shocks and baseline policy. We will find that observed heat waves since 1990 have mostly, but not entirely, hit producer-assisting markets and therefore contributed toward *lower* distortions and deadweight loss. By contrast, our projections of end-of-century climate change have a larger effect on consumer-assisting markets and therefore push toward *greater* distortions and deadweight loss. Because of this, we predict that endogenous policy adjustment will amplify welfare losses from end-of-century climate change by 14%.

5.1 Methods

We first describe the multi-crop and multi-country model that we use for quantification. We also describe our strategy of mapping to the data.

Supply, Demand, and Policy. For countries ℓ and crops k, we specify log-linear demand and supply curves

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

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

where (ϵ_d, ϵ_s) correspond respectively to the elasticities of demand and supply and f corresponds to the non-parametric damage function we estimated in Section 3.5. We assume that crop markets clear at the international level,

$$\sum_\ell q_{\ell kt} = \sum_\ell y_{\ell kt} \quad \forall\ k \tag{5.3}$$

We specify the government's policy function as a non-parametric function of extreme heat exposure, both locally and for import partners.

$$\alpha_{\ell kt} = \alpha^0_{\ell kt} + g(\text{ExtremeExposure}_{\ell kt}) + h(\text{ForeignExtremeExposure}_{\ell kt}) \tag{5.4}$$

This corresponds exactly to our estimates of Equation 4.4 visualized in Figure 7. This allows us to capture the systematic relationship between both local and foreign climate shocks and policy. As will become clear shortly, our counterfactuals will hold fixed all unmodeled determinants of policy embedded in $\alpha^0_{\ell kt}$. Directly using our regression estimate allows us to proceed without needing to estimate the government's preferences in our model and, more generally, to be robust to alternative possible models that may generate the empirical patterns in nominal rates of assistance. Finally, from the definition of the *ad valorem* tariff (i.e., NRA), the domestic price is $p_{\ell kt} = (1+\alpha_{\ell kt})p_{kt}$ in terms of the international price p_{kt}.

Measuring Welfare. We evaluate welfare in terms of consumer surplus, producer surplus, and government revenue, defined below:

$$\mathcal{C}_{\ell kt} = \frac{q^0_{\ell kt}}{1-\epsilon_d} p_{\ell kt}^{1-\epsilon_d}, \quad \mathcal{P}_{\ell kt} = \frac{y^0_{\ell kt}}{1+\epsilon_s} p_{\ell kt}^{1+\epsilon_s} e_{\ell kt}^{f(\text{ExtremeExposure})}, \quad \mathcal{R}_{\ell kt} = \frac{\alpha_{\ell kt}}{1+\alpha_{\ell kt}} p_{\ell kt}(q_{\ell kt} - y_{\ell kt}) \tag{5.5}$$

We moreover define total surplus as the equal-weighted sum of these components

$$\mathcal{S}_{\ell kt} = \mathcal{C}_{\ell kt} + \mathcal{P}_{\ell kt} + \mathcal{R}_{\ell kt} \tag{5.6}$$

Of course, as we have argued throughout this utilitarian objective may not be the welfare criterion used by governments. Nonetheless, we will use it as a "total welfare" benchmark.

Calibration. We measure ExtremeExposure$_{\ell kt}$, ForeignExtremeExposure$_{\ell kt}$, consumption $q_{\ell kt}$, production $y_{\ell kt}$, world prices p_{kt}, and domestic NRA $\alpha_{\ell kt}$ in each year from 1991 to 2010.[18] We restrict attention to the ten large crops studied by Costinot et al. (2016) and the countries for which we have data on policy. We interpret these data as generated by a realized equilibrium of our model.[19] With an external calculation of the elasticities of supply and demand (ϵ_s, ϵ_d) and the production damage of climate change (f), we can compute the time-varying demand and supply intercepts $(q^0_{\ell kt}, y^0_{\ell kt})$. We calibrate $\epsilon_d = 2.82$ and $\epsilon_s = 2.46$ based on estimates from Costinot et al. (2016) and we measure f directly by running the regression implied by the theory.[20]

To calibrate the policy rule, we use our empirical estimates from Section 4. Specifically, our calibration of g and h corresponds to the results presented in Figure 7. Directly using our regression estimate allows us to proceed without needing to estimate the government's preferences in our model and, more generally, to be robust to alternative possible models that may generate the empirical patterns in nominal rates of assistance.

[18] We cannot study our entire baseline sample, from 1980, due to availability of producer prices from the FAO only from 1991 onward.

[19] We compute unmodeled net production as total production less total consumption for the studied sub-sample of country-crop pairs, which must have NRA data. We hold this net supply fixed in counterfactuals when we calculate global market clearing.

[20] We take estimates $\theta = 2.46$ and $\kappa = 2.82$ from Table 2 in that paper.

5.2 Policy as Adaptation to Shocks

We first study how policy responses shape the welfare effects of extreme weather. That is: if governments did not systematically intervene to protect consumers during periods of agricultural stress, what would be the effects on consumers, producers, and total welfare?

To do this formally, we introduce two counterfactual scenarios which we can compare to observed outcomes. The first is a world with *no extreme heat* (NEH). We define this as a scenario in which extreme exposure is always equal to its in-sample minimum for each country-crop pair. This directly affects both supply (Equation 5.2) and policy (Equation 5.4). The second is a world with *no policy response* to extreme heat (NPR). In this scenario, we hold supply shocks as observed (i.e., with observed weather variation) but keep policy as it would be in the no extreme heat scenario. This models a world in which governments are completely neutral in response to climatic shocks. In both counterfactual scenarios, we can solve for the equilibrium consequences for prices and welfare and compare these against the equivalent from the observed (O) equilibrium. Then, for any welfare measure W, we can calculate welfare losses under unresponsive (U) and responsive (R) policy as

$$L_W^R = 100 \cdot \frac{W^O - W^{NEH}}{W^{NEH}} \qquad\qquad L_W^U = 100 \cdot \frac{W^{NPR} - W^{NEH}}{W^{NEH}} \tag{5.7}$$

These measure percent surplus losses relative to a baseline scenario with no extreme heat.

Policy and Redistribution. Table 3 summarizes our results by reporting percent losses under both policy scenarios for consumers, for producers, and in total. Panels A through D break down the findings across four groups of observations: those which experience extreme heat only domestically, those which experience extreme heat only through foreign spillovers, those which experience both shocks, and those which are not shocked at all. We describe these broken-down results first to highlight the key redistributional mechanisms, before returning to discuss the overall effect (Panel E).

For markets affected only domestically (Panel A), responsive policy offsets losses for consumers, changing a 2.71% loss to a 1.29% gain, and intensifies losses for producers, increasing a 11.31% loss into a 19.56% (i.e. exacerbating surplus losses for producers by 73%). The net welfare effect from a utilitarian perspective is essentially zero. For markets affected only via foreign spillovers (Panel B), responsive policy deepens losses for consumers and substantially amplifies gains for producers. These estimates are consistent with the discussion of India's recent policy fluctuations in the introduction: endogenous policy responses to climate shocks tend to shield losses for local consumers, while exacerbating losses for local producers and consumers around the world.

Table 3: Food Policy and Adaptation to Extreme Heat Shocks

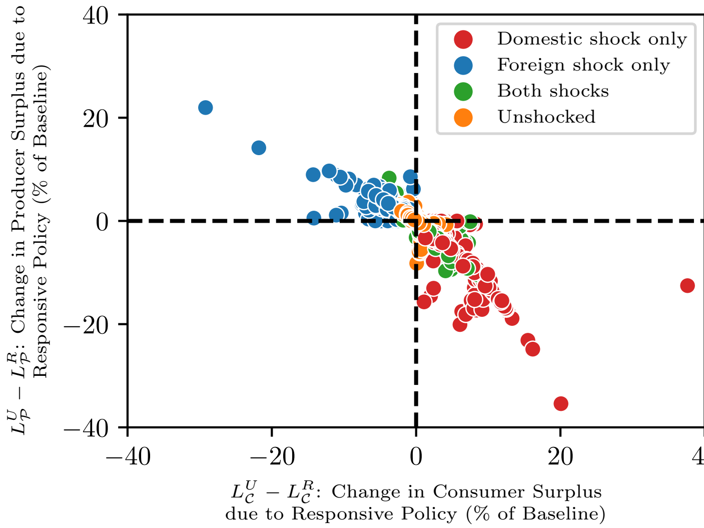
	Percent losses from extreme heat under Unresponsive Policy	Responsive Policy	Percent Difference
Panel A: Domestic Shock Only (14%)			
Consumer Surplus	-2.71	1.29	148
Producer Surplus	-11.31	-19.56	-73
Total Surplus	-5.02	-5.03	0
Panel B: Foreign Shock Only (19%)			
Consumer Surplus	-2.22	-7.52	-239
Producer Surplus	3.31	12.46	276
Total Surplus	-0.72	0.05	107
Panel C: Both Shocks (10%)			
Consumer Surplus	-3.07	-1.95	36
Producer Surplus	-11.77	-14.06	-20
Total Surplus	-2.14	-0.93	57
Panel D: Unshocked (56%)			
Consumer Surplus	-1.25	-1.24	1
Producer Surplus	2.24	2.16	2
Total Surplus	-0.32	-0.44	-37
Panel E: All Markets			
Consumer Surplus	-1.96	-2.02	-3
Producer Surplus	-2.26	-2.65	-17
Total Surplus	-1.55	-1.30	16

Notes: This table reports losses from extreme heat in consumer surplus, producer surplus, and total surplus under two policy scenarios: one that counterfactually fixes policy not to respond to extreme heat (Unresponsive Policy), and one that allows policy to adjust as observed (Responsive Policy). The "Percent Difference" is the effect attributable to responsive policy. That is, letting x_i denote the value in column i, $x_3 = 100 \cdot (x_2 - x_1)/|x_1|$. Panels A-D sum separately across crop-country-year observations in which (A) there is only domestic exposure, (B) there is only foreign exposure, (C) there is exposure on both dimensions, and (D) there is neither domestic nor import-partner exposure. Panel E sums over all countries, crops, and years.

For markets affected by both shocks (Panel C), we find that responsive policy again aids consumers at the expense of producers. But these effects are much smaller than those in Panel A for countries with only domestic shock exposure. In this way, responses to foreign shocks *dampen* the redistributive role of policy when multiple countries are shocked at once.

Finally, for markets unaffected by any shock, the switch from the unresponsive to the responsive equilibrium still reduces total welfare by 0.12 percentage points. This purely reflects

Figure 8: Responsive Policy Trades Off Consumer and Producer Welfare



Notes: This plot compares the welfare effect of responsive policy for consumers (x-axis) and producers (y-axis) in our in-sample counterfactual. Each dot is a country-crop-year "market." Positive values on each axis denote welfare improvements under responsive policy. The dots are color-coded by which shocks affect those observations, consistent with the rows of Table 3.

equilibrium effects operating through changing international prices. Thus, even "bystander" countries are affected by governments' endogenous response to climate shocks.

Taken together, our findings show the extent to which governments use policy to reallocate surplus between producers and consumers in response to shocks. To visualize this, in Figure 8 we present a scatter plot of the changes in surplus due to responsive policy for consumers and producers. Observations are color-coded by their "type" in Table 3. All observations are either in the fourth quadrant—scenarios where policy helps consumers at the expense of producers—or the second quadrant—scenarios where policy helps producers at the expense of consumers. The plot reveals how the aggregate analysis of Table 3, which averaged over each color-coded category, masked significant heterogeneity across markets. It is not uncommon for responsive policy to shift the effect of climate shocks for producers and consumers by over 10 percentage points, and in some cases over 20 percentage points.

Policy and Total Welfare. Panel E of Table 3 shows that total global utilitarian welfare slightly increases under responsive policy versus unresponsive policy. The difference is 0.25 percentage points of baseline welfare, or 16% of the loss in welfare from extreme heat under unresponsive policy. The effect of responsive policy on utilitarian welfare is not a straightforward consequence of our theory or studied mechanism, which concerned primarily

Table 4: Extreme Heat and Agricultural Distortions

		Extreme heat: Decreases α	Extreme heat: Increases α
Baseline distortion is:	Negative ($\alpha < 0$)	201 27%	558 74%
	Positive ($\alpha > 0$)	1,037 67%	523 34%

Notes: Each cell categorizes country-crop-year observations by whether the baseline price distortion α is positive or negative in the no extreme heat (NEH) scenario and whether the price distortion is higher or lower when accounting for response to extreme heat (conditional on being shocked). The counts are total observations and the percentages are row proportions. The red cells indicate distortions that increase in absolute value and the green cells indicate distortions that decrease in absolute value.

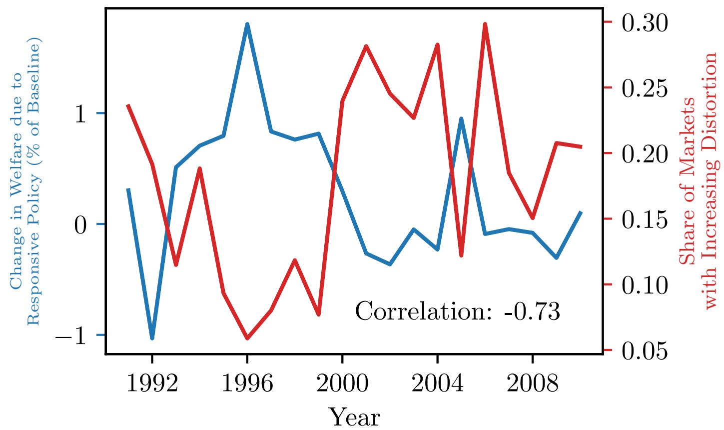
the redistribution of surplus between producers and consumers. Moreover, our main finding that policy is highly responsive to climate shocks is inconsistent with governments' maximizing utilitarian welfare (see Proposition 2); while it is an interesting benchmark, it does not seem to be the relevant one for policy makers around the world. Nevertheless, the effect on total welfare could be of interest to understand the extent to which policy adjustments contribute to "climate adaptation" globally. In particular, in a world in which countries are adjusting policy to protect some domestic constituents at the expense of others, domestically and internationally, what determines the overall effect on surplus?

The answer is that global policy adjustments can have positive or negative effects on global deadweight loss. This, in turn, hinges on the geographic distribution of climate shocks and their correlation with existing levels of distortions. To illustrate this more clearly, we present two additional pieces of evidence.

First, Table 4 categorizes observations based on the relationship between baseline levels of policy distortion (rows) and induced policy changes in a responsive world (columns), conditional on being shocked. The majority of observations are in the "off diagonal" cells, in which producer assistance is relaxed (bottom left) or consumer assistance is relaxed (top right). This means that historical heat waves have tended to hit countries with significant producer assistance and thus have contributed toward less distorted global agricultural markets.

Second, to bring this into sharper relief, we separate our total welfare calculation for each year in the sample (1991-2010) and the percent welfare improvement for responsive policy versus unresponsive policy. We also calculate, for each year, the share of markets (surplus weighted) in which distortions move further away from zero. In Figure 9, we plot

Figure 9: Welfare Consequences of Responsive Policy and Change in Distortions



Notes: The blue line (left scale) plots the global welfare improvement from responsive versus unresponsive policy from 1991 to 2010. The red line (right scale) plots the fraction of markets in which, conditional on experiencing a shock, distortions move in the same direction as their original sign. For this statistic, we average across markets weighted by their contribution toward total surplus.

these two time series together. Our finding that responsive policy improved welfare overall masks heterogeneity across years, varying from a 1 percentage point reduction to a 1.5 percentage point gain. Moreover, years in which responsive policy is welfare improving are the ones in which fewer markets experience increasing distortions (correlation: -0.73). This is consistent with a story in which responsive policy increases welfare in years when it reduces the overall level of distortions and reduces welfare in years when it increases the overall level of distortions.

5.3 Global Adaptation to Climate Change

The previous results showed that the normative consequences of climate-responsive policy depend on two key features of the driving shocks. The first is whether shocks hit countries in isolation versus many countries at once. This determines the extent to which reactions to foreign shocks dampen policy responses. The second is how the pattern of shocks relates to the existing pattern of distortions. This determines whether policy adjustment on net increases or decreases global deadweight loss.

In this subsection, we use our framework to study the effects of projected end-of-century climate change. While this exercise requires additional and more challenging assumptions about the external validity of our estimates, it offers a window into the important question of

Table 5: Food Policy and Adaptation to End-of-Century Climate Change

	Percent losses from climate change under Unresponsive Policy	Responsive Policy	Percent Difference
Panel A: All Markets			
Consumer Surplus	-2.31	-2.68	14
Producer Surplus	-1.06	-2.36	55
Total Surplus	-2.75	-3.12	-14
Panel B: More Affected Markets (10%)			
Consumer Surplus	-3.24	3.20	199
Producer Surplus	-9.54	-17.63	-85
Total Surplus	-5.32	-6.59	-24
Panel C: Less Affected Markets (90%)			
Consumer Surplus	-2.43	-4.77	-96
Producer Surplus	1.49	7.81	424
Total Surplus	-1.57	1.53	3

Notes: This table reports losses from climate change (2000s versus projected 2090s) in consumer surplus, producer surplus, and total surplus under two policy scenarios: one that counterfactually fixes policy at the 2010s level (Unresponsive Policy) and one that allows policy to adjust following in the in-sample pattern (Responsive Policy). The "Percent Difference" is the effect attributable to responsive policy. That is, letting x_i denote the value in column i, $x_3 = 100 \cdot (x_2 - x_1)/|x_1|$. Panel A sums over all countries, crops, and years. Panel B sums over markets which, for each crop are within the upper 10% tail of production losses. Panel B sums over the other markets.

how changes in agricultural policy can facilitate or undermine adaptation to climate change.

Methods. We predict Extreme Exposure at the crop-by-country level in the decade 2091-2100 under the GFDL-ESM4 model, produced by the US National Oceanic and Atmospheric Administration's Geophysical Fluid Dynamics Laboratory and included in the CMIP 6 model ensemble. To construct the estimates, we take central model forecasts from NASA's Global Daily Downscaled Projections at the 0.25 degree grid cell level, corresponding to the SSP 4.5 pathway for global greenhouse gas concentrations.[21] As in Schlenker and Roberts (2009), we estimate the within-day exposure to temperatures above any given cut-off level and translate this into estimates for the average per-year exposure to degree days above each of our crop-specific thresholds in each of our studied countries.

Following the method described earlier, we consider two time periods in this exercise. We map the first to average data from 2001-2010 ("the 2000s"). We map the second to the

[21] The data are available at https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6.

projected climate from 2091-2100. We consider two scenarios for the future: one in which policy responds to the change in climate and one in which it is held fixed at the 2000s level.

Discussion: Modeling Assumptions and Other Forms of Adaptation. The assumptions underlying our second counterfactual are, mathematically, the same ones underlying our first. Nonetheless, they take on a more challenging interpretation when extrapolating out of sample. Our calibration to the in-sample damage function and policy response functions is tantamount to assuming that long-run adaptation on various other margins (e.g., crop choice or technology) does not significantly alter the estimated relationships between temperature extremes, production, and policy distortions. On the basis of our empirical exploration of low-frequency relationships among these variables (Section 4.3), we would argue that the assumption is at least not unreasonable in recent history. But the assumption is more extreme when applied to end-of-century projections. In that sense, our analysis isolates *one* mechanism of adaptation, but obviously does not provide a comprehensive picture for how all plausible mechanisms interact.

Results. Table 5 reports welfare losses from climate change under each policy regime. Panel A focuses on the full sample of country-crop pairs. Our estimates suggest that rising temperatures will reduce global welfare by 3.12% by 2100. If policy were held fixed at the current levels, this loss would reduce to 2.75%. Thus, endogenous policy exacerbates total damage by 14%. Based on the discussion above, this suggests that out-of-sample climate change affects different markets than in-sample heat waves. We confirm this intuition in Table 6, which mirrors Table 4 from the in-sample analysis. In the climate change projection, a much larger fraction of observations are on the "diagonal" (shaded in red): they lead to increases in consumer subsidies in consumer-supporting markets or increases in producer subsidies in producer-supporting markets.

We next investigate the distributional effects of the shock, and the distributional consequences of responsive agricultural distortions, across the world. To do this, we define the 10% tail of "most affected" countries for each crop in terms of lost production. We find that more affected markets shield consumers at the expense of producers, while less affected markets do the opposite. This is consistent with our findings from the in-sample counterfactual. Our estimates suggest that responsive policy is able to entirely shield consumers from surplus losses in more-affected markets, while increasing losses for local producers by 85% and nearly doubling losses in consumer surplus in the rest of the world. Thus, endogenous food policy leads to vastly different outcomes for consumers and producers depending on the heterogeneous incidence of climate change in different parts of the world.

Table 6: Climate Change and Agricultural Distortions

		Climate change (2090s): Decreases α	Climate change (2090s): Increases α
Baseline distortion (2010s) is:	Negative ($\alpha < 0$)	43 63%	25 37%
	Positive ($\alpha > 0$)	101 51%	96 49%

Notes: Each cell categorizes country-crop-year observations by whether the baseline price distortion α is positive or negative in the 2010s and whether the price distortion predicted to increase or decrease under the 2090s climate (conditional on being shocked at all). The counts are total observations and the percentages are row proportions. The red cells indicate distortions that increase in absolute value and the green cells indicate distortions that decrease in absolute value.

6 Conclusion

While international leaders in policy making proclaim that "food security rests on trade," a growing number of examples suggest that governments are willing to alter food policy and restrict trade in response to climate shocks to productivity (Gurria and da Silva, 2019). These policy responses can lead to "shortages of essential foods" and price spikes around the world, potentially exacerbating the consequences global warming (Ghosal et al., 2023).

We begin with a model to show how distributional concerns can motivate distortionary agricultural policy. The response of this policy to climatic productivity shocks is ambiguous *ex ante* and hinges on the government's relative preferences for constituent well-being and government revenue. Moreover, contrary to the popular narrative, the overall welfare consequences of responsive policy is also ambiguous: it hinges on the distribution of climate shocks across markets and whether they increase or decrease the overall level of distortions in the agricultural economy. Therefore, to understand the interaction between climate change and agricultural policy, it is essential to turn to data.

We construct a new global panel dataset of crop-specific extreme heat exposure, production, trade, and policy distortions since 1980. We find that extreme heat exposure shifts policy in a pro-consumer direction, in both the short-run and long-run. Consistent with our model, extreme heat exposure to import partners has the opposite effect, stabilizing the global impact of temperature on policy. The results are most pronounced during elections, when politicians are perhaps especially attuned to the demands of their constituents.

Finally, we combine theory and data to understand how responsive policy shapes global adaptation. In sample, policy is effective at shielding consumers in the most affected areas, at the cost of amplifying damages for producers in the most climate-damaged parts of the world and consumers in the rest of the world. When we extrapolate our results to study end-of-century climate change, we find that responsive policy amplifies total damages by 14% because "adaptation via policy" increases distortions and deadweight loss on net. Together, these results highlight how climate change affects economic policy, and how economic policy in turn mediates the consequences of climate change.

References

Adão, R., Costinot, A., Donaldson, D., and Sturm, J. (2023). Why is trade not free? A revealed preference approach.

Akhmedov, A. and Zhuravskaya, E. (2004). Opportunistic political cycles: Test in a young democracy setting. *Quarterly Journal of Economics*, 119(4):1301–1338.

Alesina, A. and Roubini, N. (1992). Political cycles in OECD economies. *Review of Economic Studies*, 59(4):663–688.

Anderson, K., editor (2009). *Distortions to Agricultural Incentives: A Global Perspective*. Palgrave Macmillan.

Anderson, K., Rausser, G., and Swinnen, J. (2013). Political economy of public policies: insights from distortions to agricultural and food markets. *Journal of Economic Literature*, 51(2):423–477.

Anderson, K. and Valenzuela, E. (2008). Estimates of global distortions to agricultural incentives, 1955 to 2007. *World Bank, Washington, DC*.

Balboni, C., Burgess, R., Heil, A., Old, J., and Olken, B. (2021). Cycles of fire? Politics and forest burning in Indonesia. *AEA Papers and Proceedings*, 111:415–419.

Baldos, U., Hertel, T., and Moore, F. (2019). Understanding the spatial distribution of welfare impacts of global warming on agriculture and its drivers. *American Journal of Agricultural Economics*, 101(5):1455–1472.

Baldwin, R. (1989). The political economy of trade policy. *Journal of Economic Perspectives*, 3(4):119–135.

Bastos, P., Straume, O. R., and Urrego, J. (2013). Rain, agriculture, and tariffs. *Journal of International Economics*, 90(2):364–377.

Bates, R. (2014). *Markets and States in Tropical Africa: The Political Basis of Agricultural Policies*. Univ of California Press.

Beck, T., Clarke, G., Groff, A., Keefer, P., and Walsh, P. (2001). New tools in comparative political economy: The database of political institutions. *World Bank Economic Review*, 15(1):165–176.

Beillard, M. and Singh, S. (2022). Extreme temperatures scorch indian wheat production. Attaché Report (GAIN) IN2022-0045, USDA Foreign Agricultural Service.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40.

Carleton, T., Crews, L., and Nath, I. (2022). Agriculture, trade, and the spatial efficiency of global water use.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1):205–248.

Cruz, J.-L. and Rossi-Hansberg, E. (2023). The economic geography of global warming. *Review of Economic Studies*.

de Guzman, C. (2022). Climate crisis is driving food nationalism and changing global trade. *Time Magazine*.

Dell, M., Jones, B., and Olken, B. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Fajgelbaum, P., Goldberg, P., Kennedy, P., and Khandelwal, A. (2020). The return to protectionism. *Quarterly Journal of Economics*, 135(1):1–55.

Gawande, K. and Krishna, P. (2003). The political economy of trade policy: Empirical approaches. Handbook of International Economics, chapter 8, pages 212–250. Blackwell Publishing.

Ghosal, A., Musambi, E., and Calupitan, J. (2023). Food prices are rising as countries limit exports. Blame climate change, El Nino and Russia's war. *AP News*.

Goldberg, P. and Maggi, G. (1999). Protection for sale: An empirical investigation. *American Economic Review*, 89(5):1135–1155.

Gouel, C. and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*, 106:102408.

Grierson, W. (2001). Role of temperature in the physiology of crop plants: pre-and postharvest. In *Handbook of Plant and Crop Physiology*, pages 35–56. CRC Press.

Grossman, G. and Helpman, E. (1994). Protection for sale. *American Economic Review*, 84(4):833–850.

Grossman, G. and Helpman, E. (1995). Trade wars and trade talks. *Journal of Political Economy*, 103(4):675–708.

Gurria, A. and da Silva, J. G. (2019). Food security rests on trade. *OECD News*.

Hijmans, R., Guarino, L., Cruz, M., and Rojas, E. (2001). Computer tools for spatial analysis of plant genetic resources data: 1. DIVA-GIS. *Plant Genetic Resources Newsletter*, pages 15–19.

Hodges, T. (1990). *Predicting crop phenology.* CRC Press.

Hsiao, A. (2023). Coordination and commitment in international climate action: Evidence from palm oil.

Hultgren, A., Carleton, T., Delgado, M., Gergel, D., Greenstone, M., Houser, T., Hsiang, S., Jina, A., Kopp, R., Malevich, S., McCusker, K., Mayer, T., Nath, I., Rising, J., Rode, A., and Yuan, J. (2022). Estimating global impacts to agriculture from climate change accounting for adaptation.

Hummel, M., Hallahan, B., Brychkova, G., Ramirez-Villegas, J., Guwela, V., Chataika, B., Curley, E., McKeown, P., Morrison, L., Talsma, E., et al. (2018). Reduction in nutritional quality and growing area suitability of common bean under climate change induced drought stress in africa. *Scientific Reports*, 8(1):16187.

India Today Television (2022). Dr. Ashok Gulati calls govt's decision to ban export of wheat as anti-farmer. *India Today.*

Johnson, D. G., editor (1991). *World Agriculture in Disarray.* St. Martin's Press, 2 edition.

Kim, H., Hyun, S. W., Hoogenboom, G., Porter, C., and Kim, K. S. (2018). Fuzzy union to assess climate suitability of annual ryegrass (lolium multiflorum), alfalfa (medicago sativa) and sorghum (sorghum bicolor). *Scientific Reports*, 8(1):10220.

Krueger, A. O., Schiff, M., and Valdés, A. (1988). Agricultural incentives in developing countries: Measuring the effect of sectoral and economywide policies. *The World Bank Economic Review*, 2(3):255–271.

Lobell, D. and Field, C. (2007). Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, 2(1):014002.

Lobell, D., Schlenker, W., and Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, 333(6042):616–620.

Lockett, H. and Fildes, N. (2022). Wheat prices rise almost 6 *Financial Times.*

Monfreda, C., Ramankutty, N., and Foley, J. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, 22(1).

Moscona, J. and Sastry, K. (2023). Does directed innovation mitigate climate damage? Evidence from US agriculture. *Quarterly Journal of Economics*, 138(2):637–701.

Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., et al. (2021). Era5-land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9):4349–4383.

Nath, I. (2023). Climate change, the food problem, and the challenge of adaptation through sectoral reallocation.

Nordhaus, W. (1975). The political business cycle. *Review of Economic Studies*, 42(2):169–190.

Ramirez-Villegas, J., Jarvis, A., and Läderach, P. (2013). Empirical approaches for assessing impacts of climate change on agriculture: The EcoCrop model and a case study with grain sorghum. *Agricultural and Forest Meteorology*, 170:67–78.

Ramsey, F. (1927). A contribution to the theory of taxation. *Economic Journal*, 37(145):47–61.

Randhir, T. O. and Hertel, T. W. (2000). Trade liberalization as a vehicle for adapting to global warming. *Agricultural and Resource Economics Review*, 29(2):159–172.

Reilly, J. and Hohmann, N. (1993). Climate change and agriculture: the role of international trade. *The American Economic Review*, 83(2):306–312.

Ritchie, J. T. and Nesmith, D. S. (1991). *Temperature and Crop Development*, chapter 2, pages 5–29. John Wiley & Sons, Ltd.

Rodrik, D. (1995). Political economy of trade policy. volume 3 of *Handbook of International Economics*, chapter 28, pages 1457–1494. Elsevier.

Rogoff, K. (1990). Equilibrium political budget cycles. *American Economic Review*, 80:21–36.

Rosenzweig, C. and Parry, M. L. (1994). Potential impact of climate change on world food supply. *Nature*, 367(6459):133–138.

Rudik, I., Lyn, G., Tan, W., and Ortiz-Bobea, A. (2022). The economic effects of climate change in dynamic spatial equilibrium.

Schlenker, W. and Roberts, M. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37):15594–15598.

Yasir, S. and Kim, V. (2022). India bans most wheat exports, adding to concerns of global food insecurity. *New York Times*.

Online Appendix for: Food Policy in a Warming World

A Omitted Proofs

A.1 Proof of Proposition 1

We proceed by deriving the optimal tariff under the assumption that it is interior; at the end, we show that the assumption $\epsilon_m \notin (0, -1)$ is sufficient to guarantee interiority.

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

$$\frac{\partial Q(p)}{\partial p}|_{p=p^*}\frac{\partial p^*}{\partial \tau} = \frac{\partial Y(p)}{\partial p}|_{p=p^*}\frac{\partial p^*}{\partial \tau} + \frac{\partial M(p)}{\partial p}|_{p=p^*-\tau}\left(\frac{\partial p^*}{\partial \tau} - 1\right) \tag{A.1}$$

Re-arranging, and suppressing the evaluations, we obtain

$$\frac{\partial p^*}{\partial \tau} = -\frac{\frac{\partial M(p)}{\partial p}}{\frac{\partial Q(p)}{\partial p} - \frac{\partial Y(p)}{\partial p} - \frac{\partial M(p)}{\partial p}} = -\frac{\epsilon_m s}{-\epsilon_d\left(1 - \frac{\tau}{p^*}\right) - \left((1-s)\epsilon_s\left(1 - \frac{\tau}{p^*}\right) + s\epsilon_m\right)} \tag{A.2}$$

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

A necessary condition for optimality of an interior tariff is that the first-order benefit of changing τ is zero. That is,

$$0 = \frac{\partial P^*(\tau,\omega,\omega')}{\partial \tau}\left(-\lambda^C x + \lambda^P y\right) + \lambda^G m + \lambda^G \tau \frac{\partial M(p^* - \tau, \omega')}{\partial p}\left(\frac{\partial P^*(\tau,\omega,\omega')}{\partial \tau} - 1\right) \tag{A.3}$$

The first term measures marginal redistribution between producers and consumers. Raising τ raises domestic prices, which benefits producers in proportion to their production and hurts consumers in proportion to their consumption. The second and third terms measure the marginal changes in government revenue.

We next re-arrange Equation A.3 in the following way:

$$\tau = \frac{\frac{\partial p^*(\tau)}{\partial \tau}\left(\lambda^P Y(p^*(\tau)) - \lambda^C Q(p^*(\tau))\right) + \lambda^G M(p^*(\tau) - \tau)}{\lambda^G \frac{\partial M(p^*(\tau)-\tau)}{\partial p}\left(1 - \frac{\partial p^*(\tau)}{\partial \tau}\right)} \tag{A.4}$$

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

$$\tau = \frac{-\frac{\epsilon_m s}{-\epsilon_d\left(1-\frac{\tau}{p^*}\right)-\left((1-s)\epsilon_s\left(1-\frac{\tau}{p^*}\right)+s\epsilon_m\right)}\left(\lambda^P Y(p^*(\tau))-\lambda^C Q(p^*(\tau))\right)+\lambda^G M(p^*(\tau)-\tau)}{\left(1-\frac{\tau}{p^*}\right)\lambda^G\left(\epsilon_m\frac{M(p^*-\tau)}{p^*-\tau}\right)\frac{\epsilon_d-(1-s)\epsilon_s}{-\epsilon_d\left(1-\frac{\tau}{p^*}\right)-\left((1-s)\epsilon_s\left(1-\frac{\tau}{p^*}\right)+s\epsilon_m\right)}} \tag{A.5}$$

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

$$\frac{\tau}{p^*} = \frac{s\left(\lambda^P Y(p^*(\tau))-\lambda^C Q(p^*(\tau))\right)}{\lambda^G M(p^*(\tau)-\tau)((1-s)\epsilon_s+\epsilon_d)} - \frac{-\epsilon_d\left(1-\frac{\tau}{p^*}\right)-\left((1-s)\epsilon_s\left(1-\frac{\tau}{p^*}\right)+s\epsilon_m\right)}{\epsilon_m((1-s)\epsilon_s+\epsilon_d)} \tag{A.6}$$

For the first term, we divide through by domestic consumption x to put everything in terms of import fractions:

$$\frac{\tau}{p^*} = \frac{\lambda^P(1-s)-\lambda^C}{\lambda^G((1-s)\epsilon_s+\epsilon_d)} - \frac{\epsilon_d\left(1-\frac{\tau}{p^*}\right)-\left((1-s)\epsilon_s\left(1-\frac{\tau}{p^*}\right)+s\epsilon_m\right)}{\epsilon_m((1-s)\epsilon_s+\epsilon_d)} \tag{A.7}$$

For the second term, we split the numerator and cancel to obtain:

$$\frac{\tau}{p^*} = \frac{\lambda^P(1-s)-\lambda^C}{\lambda^G((1-s)\epsilon_s+\epsilon_d)} + \frac{1}{\epsilon_m}\left(1-\frac{\tau}{p^*}\right) + \frac{s}{(1-s)\epsilon_s+\epsilon_d} \tag{A.8}$$

Finally, we take τ/p^* to the right-hand side and combine fractions to obtain, as desired,

$$\frac{\tau}{p^*} = \frac{\epsilon_m}{\epsilon_m+1}\left(\frac{\lambda^P(1-s)+\lambda^G s-\lambda^C}{\lambda^G((1-s)\epsilon_s+\epsilon_d)}\right) + \frac{1}{\epsilon_m+1} \tag{A.9}$$

Equation 2.2 follows by defining

$$\alpha = \frac{\tau}{p^*-\tau} \tag{A.10}$$

We next check that the conjectured solution lies in the correct domain, or $\alpha > -1$ (i.e., the true solution is not a corner solution). To do this, we write the condition

$$\frac{1}{\epsilon_m}\left(\frac{\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right)+\epsilon_m\left(\lambda^P(1-s)+\lambda^G s-\lambda^C\right)}{\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right)-\left(\lambda^P(1-s)+\lambda^G s-\lambda^C\right)}\right) > -1 \tag{A.11}$$

Multiplying both sides by $\epsilon_m s > 0$, we obtain

$$\frac{s\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right)+s\epsilon_m\left(\lambda^P(1-s)+\lambda^G s-\lambda^C\right)}{\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right)-\left(\lambda^P(1-s)+\lambda^G s-\lambda^C\right)} > -\epsilon_m s \tag{A.12}$$

We now split cases. If the denominator is positive, we obtain

$$\begin{aligned} s\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right) + s\epsilon_m\left(\lambda^P(1-s)+\lambda^G s-\lambda^C\right) > \\ -\epsilon_m s\left(\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right)-\left(\lambda^P(1-s)+\lambda^G s-\lambda^C\right)\right) \end{aligned} \tag{A.13}$$

Or

$$s\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right) > -\epsilon_m s\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right) \tag{A.14}$$

or $s > -s\epsilon_m$. If $\epsilon_m, s > 0$, this is immediate. If $\epsilon_m, s < 0$, then the condition is $\epsilon_m < -1$. This is consistent with our assumption.

If the denominator is negative, we obtain $s < s\epsilon_m$. If $\epsilon_m, s < 0$, this is immediate. If $\epsilon_m, s > 0$, then this condition requires $\epsilon_m > 1$. This is also consistent with our assumption.

A.2 Proof of Corollary 1

Since $p^* - \tau > 0$ and $\epsilon_m > 0$, we have that

$$\text{sign}[\alpha^*] = \text{sign}\left[\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right)+\epsilon_m\left(\lambda^P(1-s)+\lambda^G s-\lambda^C\right)\right] \tag{A.15}$$

The claimed expression follows immediately.

A.3 Proof of Proposition 2

We first and state and prove two auxiliary Lemmas:

Lemma 1. *A pair (α^*, s^*) constitutes an equilibrium if*

$$\begin{aligned} \alpha^* &= A(s^*) \\ s^* &= S(\alpha^*, \omega, \omega') \end{aligned} \tag{A.16}$$

where (i) $\frac{\partial S}{\partial \alpha} < 0$, (ii) S increases in ω, (iii) S decreases in ω', and (iv) $\alpha^* = A(s^*)$ crosses $\alpha = S^{-1}(s^*; \omega, \omega')$ once from below.

Proof. Property (i): From market clearing,

$$Q(p^*) = Y(p^*, \omega) + M\left(\frac{p^*}{1+\alpha}, \omega'\right) \tag{A.17}$$

and the fact that M is increasing, 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 $1 - Y/Q$ decreases in α. Differentiability follows from the differentiability of Y, Q and P^*.

Property (ii): We observe that, using market clearing, an equivalent expression for S is

$$S(\alpha, \omega, \omega') = \frac{M\left(\frac{P^*(\alpha,\omega,\omega')}{1+\alpha}, \omega'\right)}{Q(P^*(\alpha, \omega, \omega'))} \tag{A.18}$$

Consider some $\omega_1 > \omega_0$. Under iso-elastic demand, and if $m > 0$,

$$\frac{S(\alpha, \omega_1, \omega')}{S(\alpha, \omega_0, \omega')} = \frac{\left(\frac{P^*(\alpha,\omega_1,\omega')}{P^*(\alpha,\omega_0,\omega')}\right)^{\epsilon_m}}{\left(\frac{P^*(\alpha,\omega_1,\omega')}{P^*(\alpha,\omega_0,\omega')}\right)^{-\epsilon_d}} = \left(\frac{P^*(\alpha, \omega_1, \omega')}{P^*(\alpha, \omega_0, \omega')}\right)^{\epsilon_m+\epsilon_d} \tag{A.19}$$

which is > 1 given the observation that P^* increases in ω. If $m < 0$,

$$\frac{S(\alpha, \omega_1, \omega')}{S(\alpha, \omega_0, \omega')} = \left(\frac{P^*(\alpha, \omega_1, \omega')}{P^*(\alpha, \omega_0, \omega')}\right)^{-\epsilon_m+\epsilon_d} \tag{A.20}$$

which is > 1 under the additional assumption that $\epsilon_m > \epsilon_d$, or foreign demand is more elastic than domestic demand.

Property (iii): This follows from the same logic as the comparative static in α, as the variables enter M with the same sign.

Property (iv): By direct calculation,

$$\frac{\partial S}{\partial \alpha} = -\frac{(1-s)s\epsilon_m(\epsilon_s + \epsilon_d)}{(1-s)\epsilon_s + s\epsilon_m + \epsilon_d}\frac{1}{(1+\alpha)} < 0 \tag{A.21}$$

where the inequality uses $s\epsilon_m > 0$ 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. But this is a contradiction.

□

Lemma 2 (Relative Assistance and Import Shares)**.** *The following statements are true:*

1. *If the government is revenue-focused, or* $\epsilon_s(\lambda^C - \lambda^G) + \epsilon_d(\lambda^P - \lambda^G) < 0$, *then* $A^{*'} > 0$, *or higher import shares are associated with higher producer assistance.*

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

Proof. By direct calculation, we have that

$$\frac{\mathrm{d}A^*(s)}{\mathrm{d}s} = \frac{\left(\lambda^G(\epsilon_s+\epsilon_d) - \lambda^C\epsilon_s - \lambda^P\epsilon_d\right)(1+\epsilon_m)\lambda_G}{\epsilon_m\left(\lambda^G\left((1-s)\epsilon_s+\epsilon_d\right) - \left(\lambda^P(1-s)+\lambda^G s - \lambda^C\right)\right)^2} \tag{A.22}$$

Thus, if the claimed condition holds, then $\partial A^*(s)/\partial s < 0$. 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. □

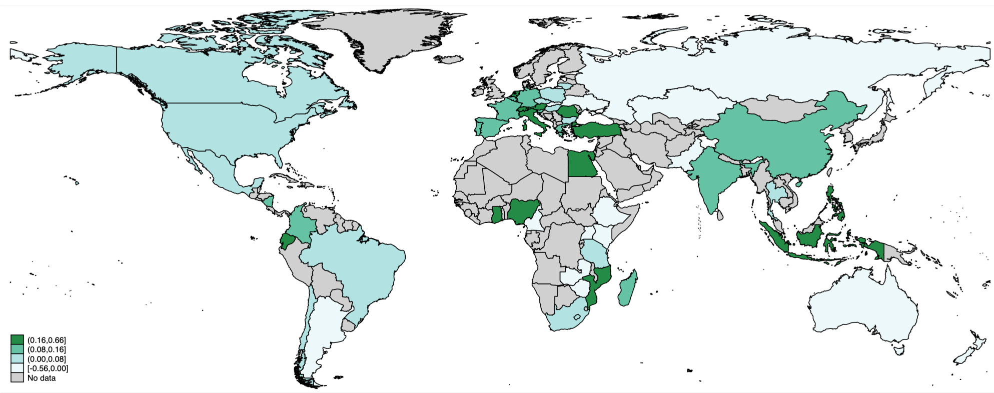
We prove the cases in turn. For all cases, we observe that for $\omega_1 \geq \omega_0$ and $\omega_1' \geq \omega_0'$, then $S(\alpha, \omega_1, \omega_1') \geq S(\alpha, \omega_0, \omega_0')$ for all α. We let α_1^*, α_0^* denote the equilibrium policy in each case. We observe that $\alpha \mapsto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

1. Since $A(s)$ is strictly increasing (Lemma 2), 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 $\alpha_1^* = A(s_{m,1}^*) \geq \alpha_0^*$.
2. Since $A(s)$ is strictly decreasing (Lemma 2), 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 $\alpha_1^* = A(s_{m,1}^*) \leq \alpha_0^*$.
3. In this case, $A(s)$ is constant (Lemma 2). Thus, $\alpha_1^* = \alpha_0^*$.

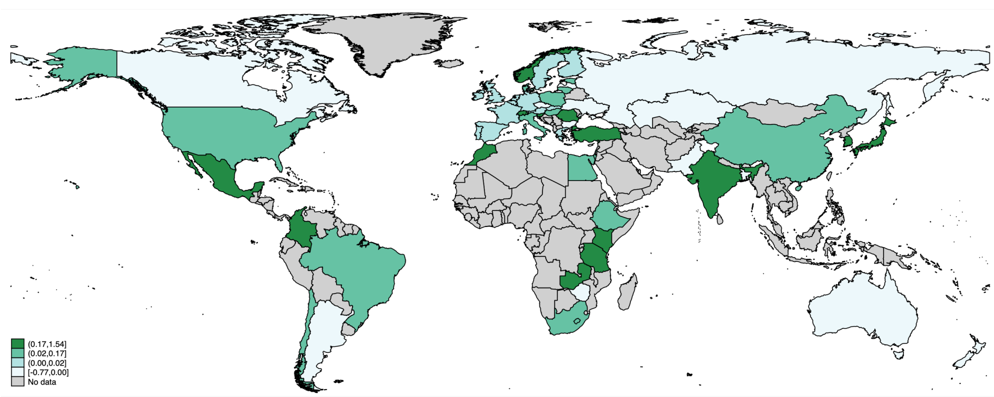
B Additional Figures and Tables

Figure A.1: Global Policy Variation for Select Crops

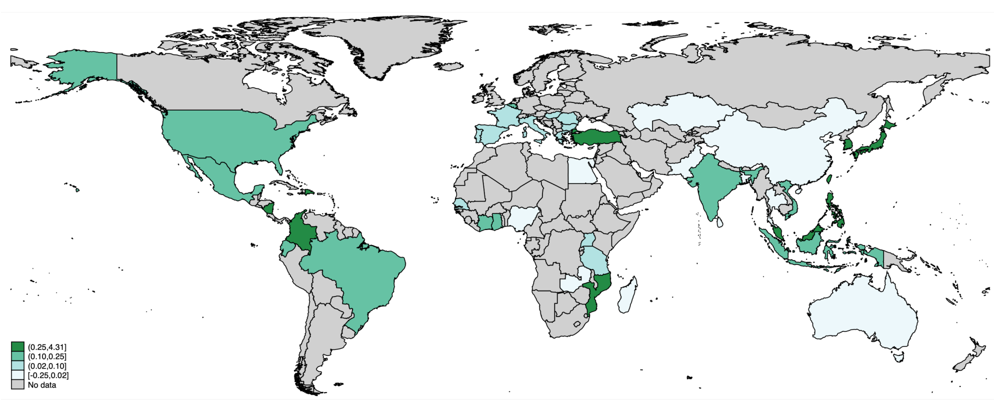
(a) Maize



(b) Wheat



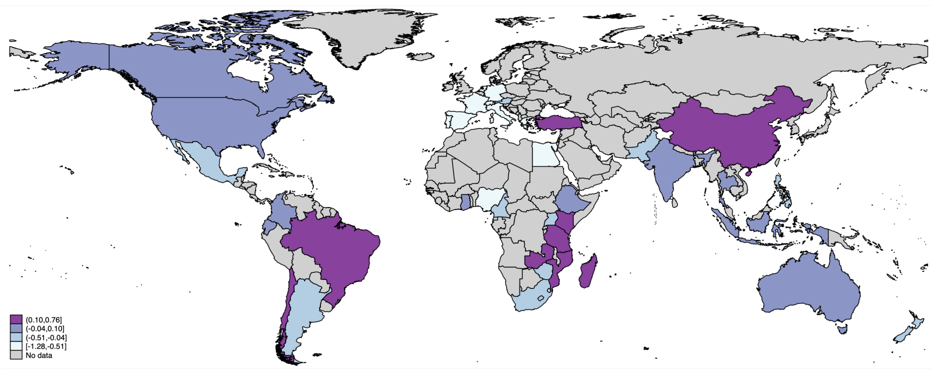
(c) Rice



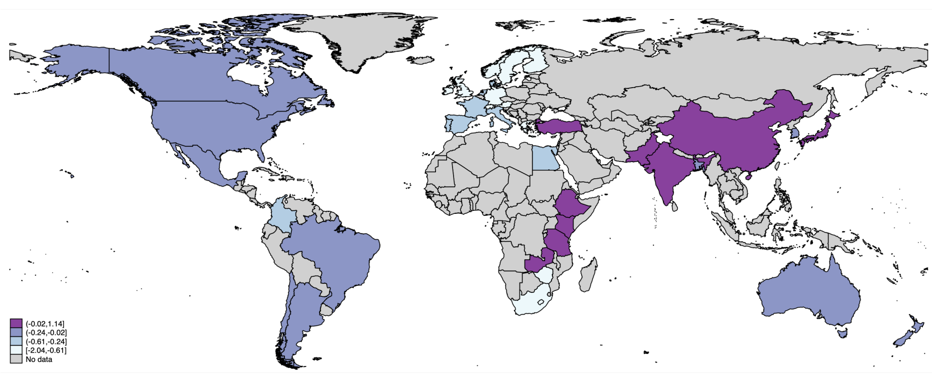
Notes: This figure displays the value of NRA for maize (Figure A.1a), wheat (Figure A.1b), and rice (Figure A.1c) averaged from 2001-2010. Countries are color-coded by quartile where darker colors correspond to larger values of NRA.

Figure A.2: Global Changes in Policy for Select Crops

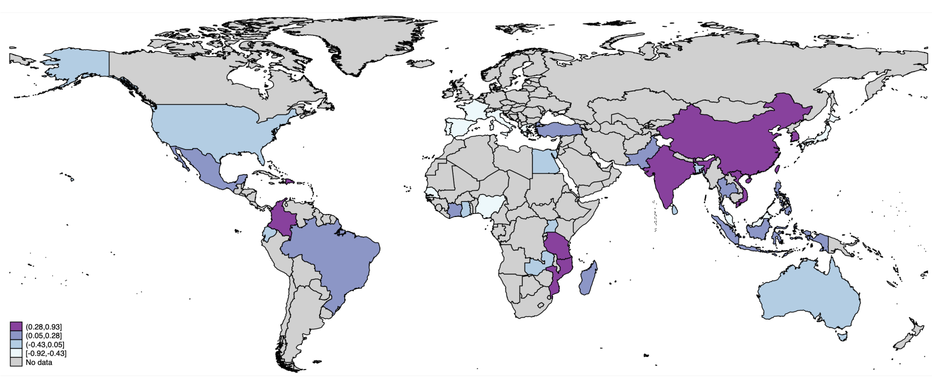
(a) Maize



(b) Wheat



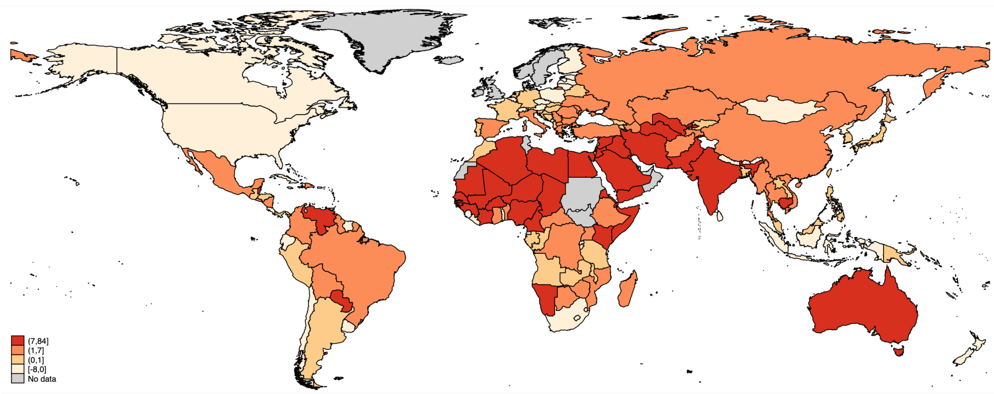
(c) Rice



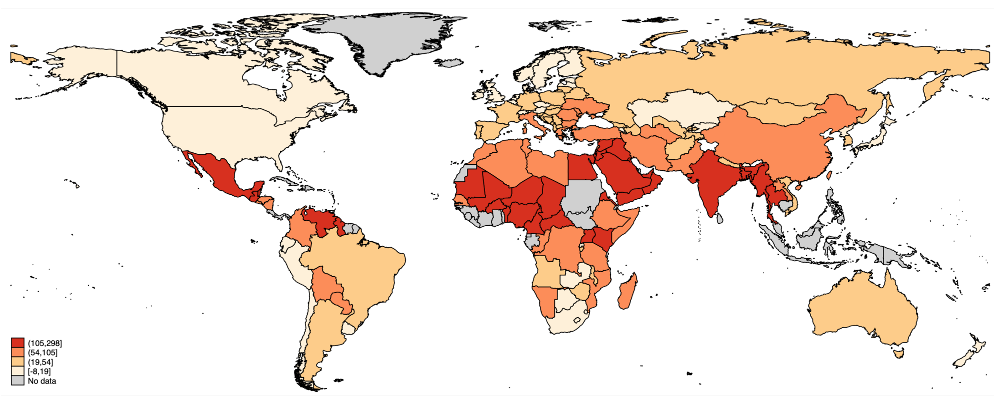
This figure displays the change in NRA (1980s-2000s) for maize (Figure A.2a), wheat (Figure A.2b), and rice (Figure A.2c). Countries are color-coded by quartile where darker colors correspond to larger values of NRA change.

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

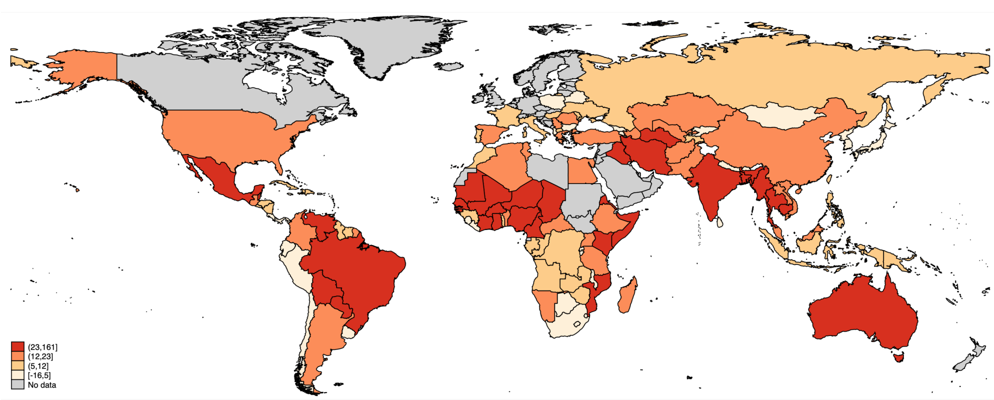
(a) Maize



(b) Wheat



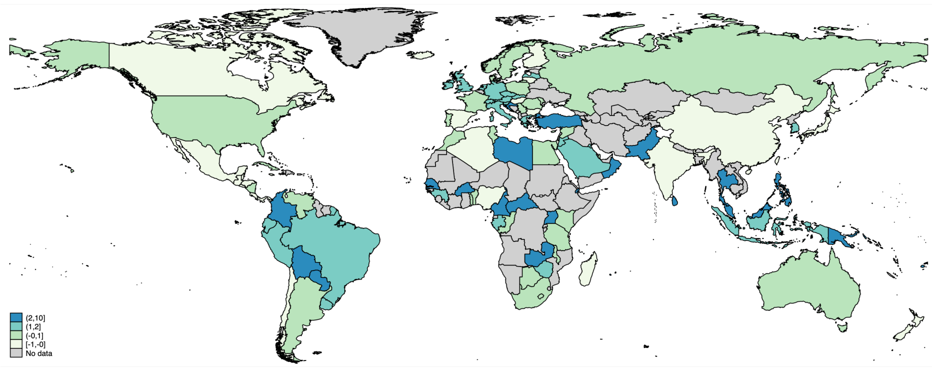
(c) Rice



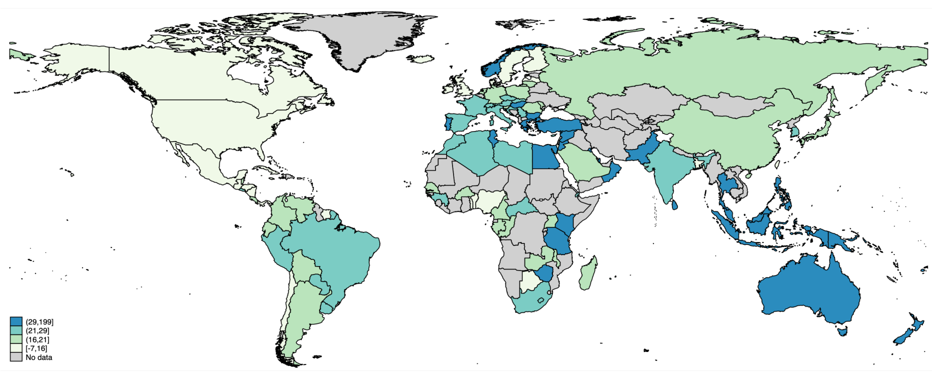
Notes: This figure displays the change in extreme heat exposure for maize (Figure A.3a), wheat (Figure A.3b), and rice (Figure A.3c) between the 1980s and the 2010s. Countries are color-coded by quartile where darker colors correspond to larger increases in extreme heat exposure.

Figure A.4: Global Changes Exposure to Foreign Extreme Temperatures

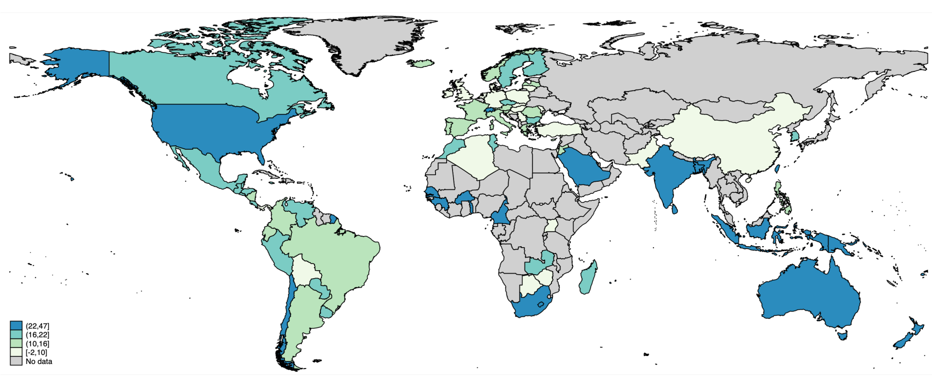
(a) Maize



(b) Wheat

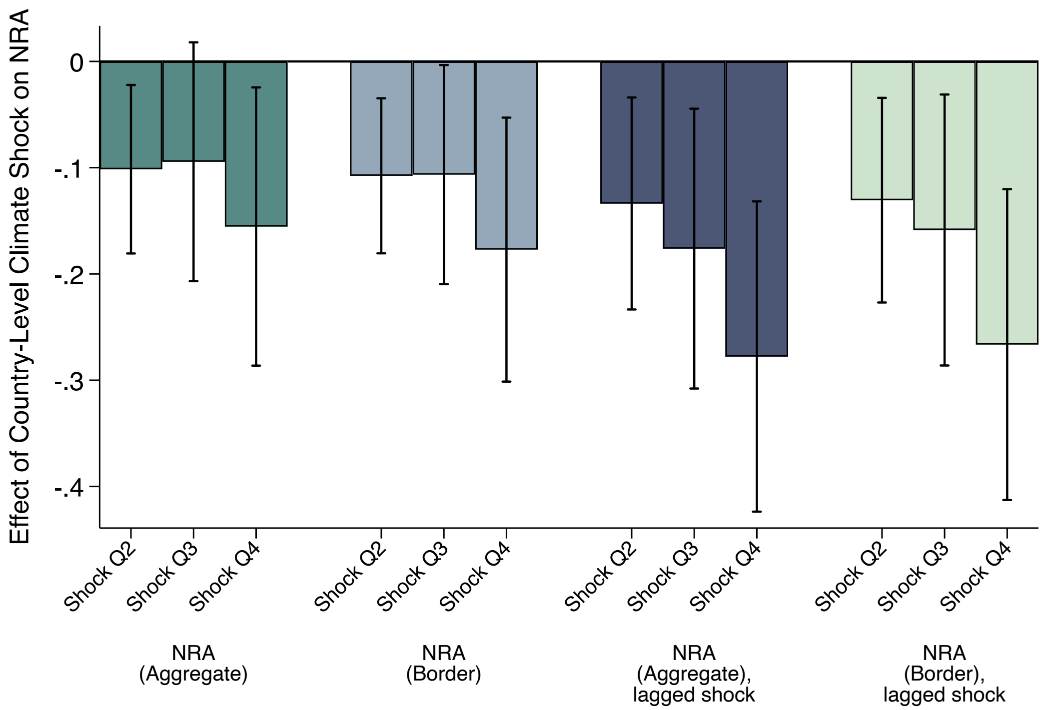


(c) Rice



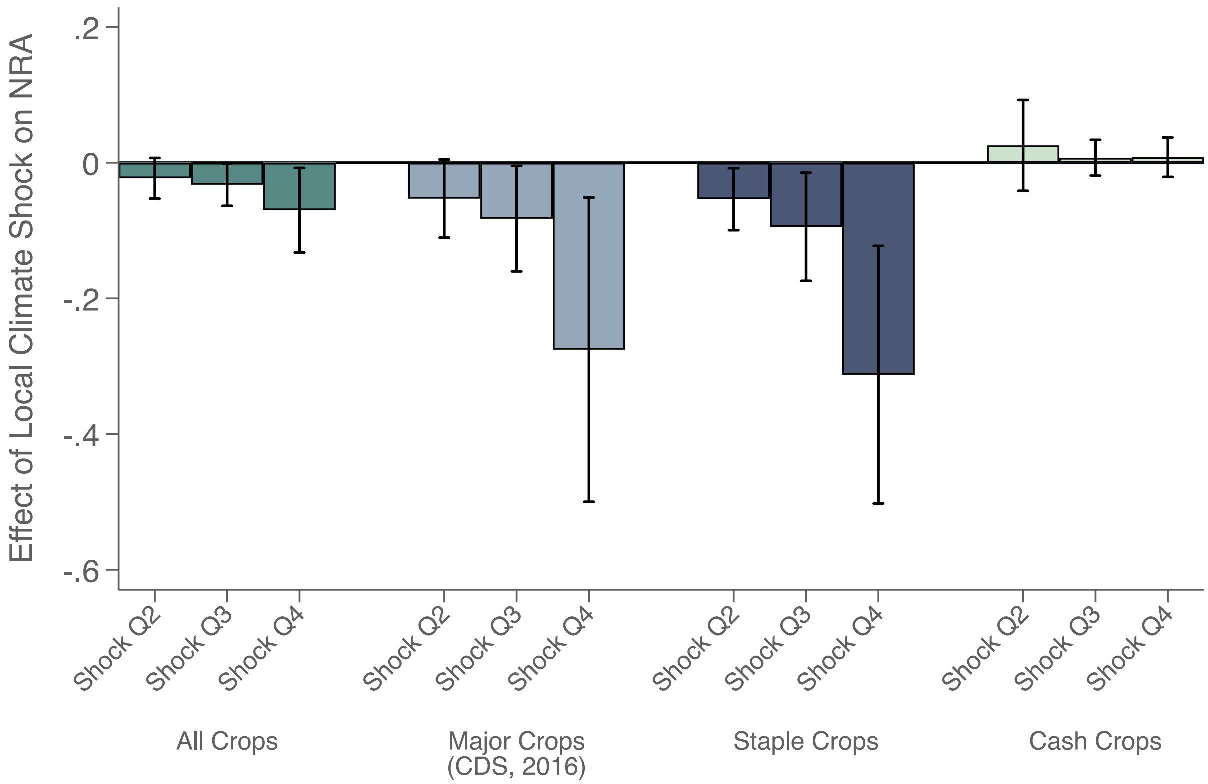
This figure displays the change in foreign import-weighted extreme heat exposure (1980s-2000s) for maize (Figure A.4a), wheat (Figure A.4b), and rice (Figure A.4c). Countries are color-coded by quartile.

Figure A.5: Extreme Heat and Agricultural Policy: Country-Year Estimates



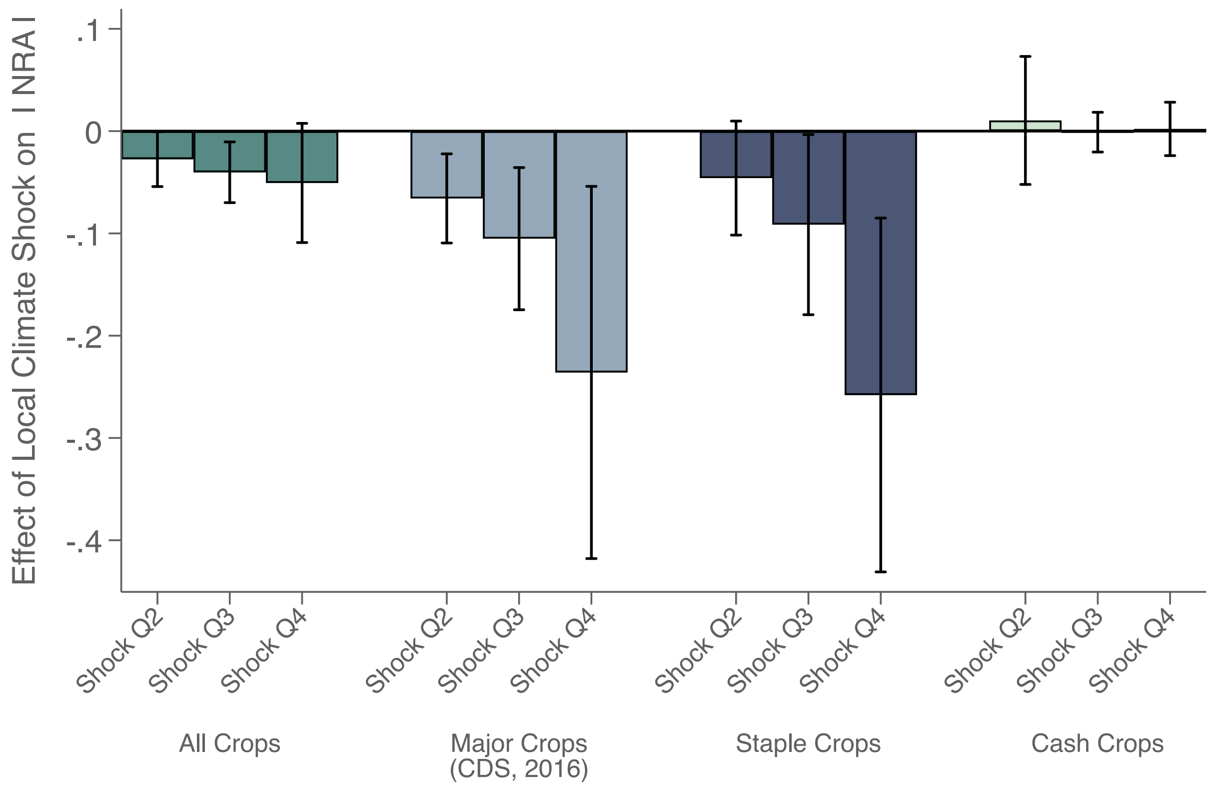
Notes: This figure displays the relationship between quartiles of extreme heat exposure and NRA. The unit of observation is a country-year and both country and year fixed effects are included. Each set of three bars corresponds to estimates from a single regression. We report 90% confidence intervals.

Figure A.6: Extreme Heat and Agricultural Policy, 1955-2011



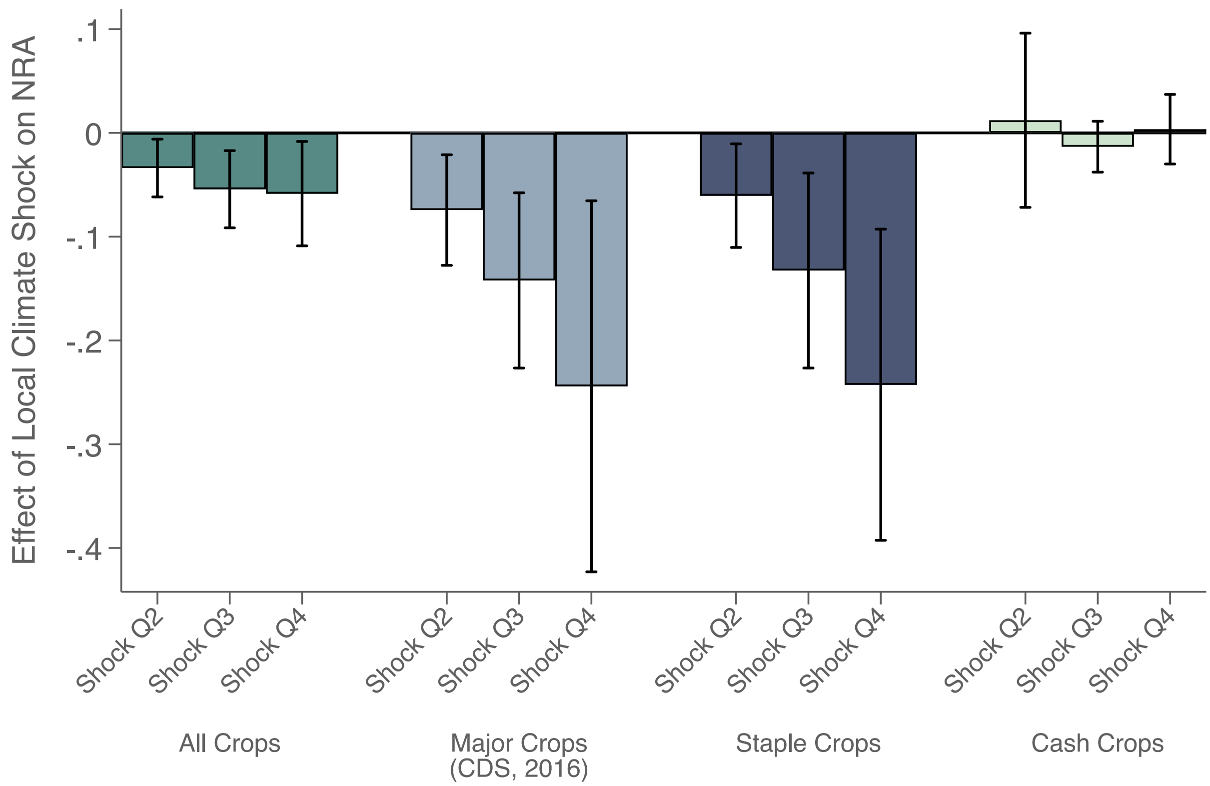
This figure displays the relationship between quartiles of extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each set of three bars corresponds to estimates from a single regression. The sample of crops included in each regression is noted below each set of bars. The sample includes all NRA and temperature data from 1955-2011. We report 90% confidence intervals.

Figure A.7: Extreme Heat and Agricultural Policy, 1980-2021 with Alternative Data



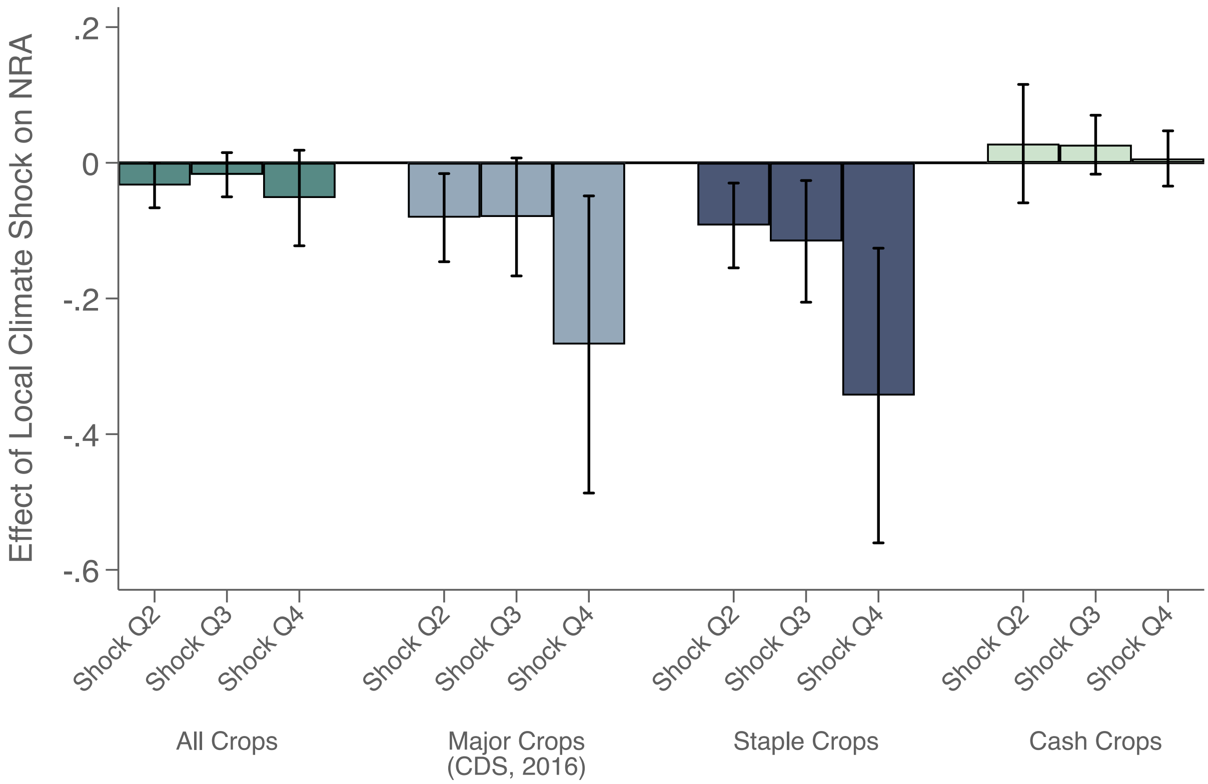
This figure displays the relationship between quartiles of extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each set of three bars corresponds to estimates from a single regression. The sample of crops included in each regression is noted below each set of bars. The sample includes all NRA and temperature from 1980 to 2021, where recent years are filled in using data from Ag-Incentives (https://www.agincentives.org/). We report 90% confidence intervals.

Figure A.8: Extreme Heat and Agricultural Policy Excluding 1980s



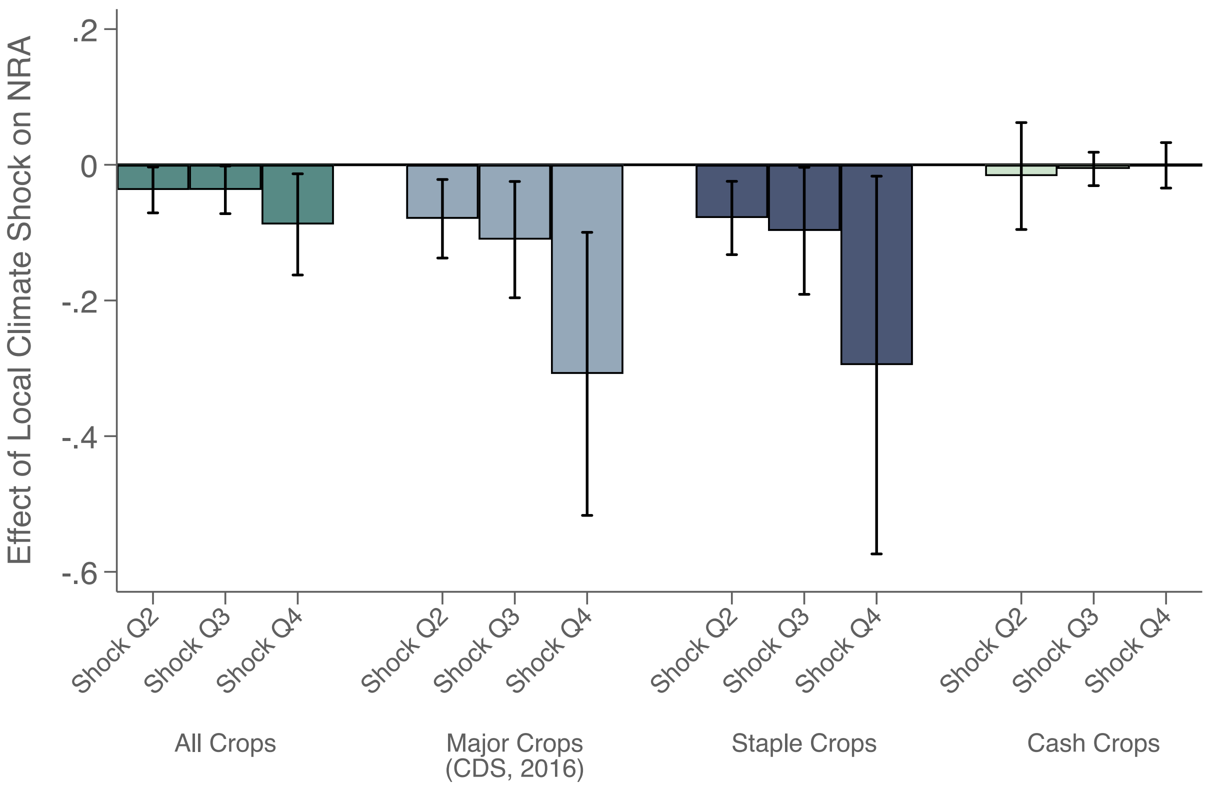
This figure displays the relationship between quartiles of extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each set of three bars corresponds to estimates from a single regression. The sample of crops included in each regression is noted below each set of bars. The 1980s are excluded from the sample. We report 90% confidence intervals.

Figure A.9: Extreme Heat and Agricultural Policy Excluding 1990s



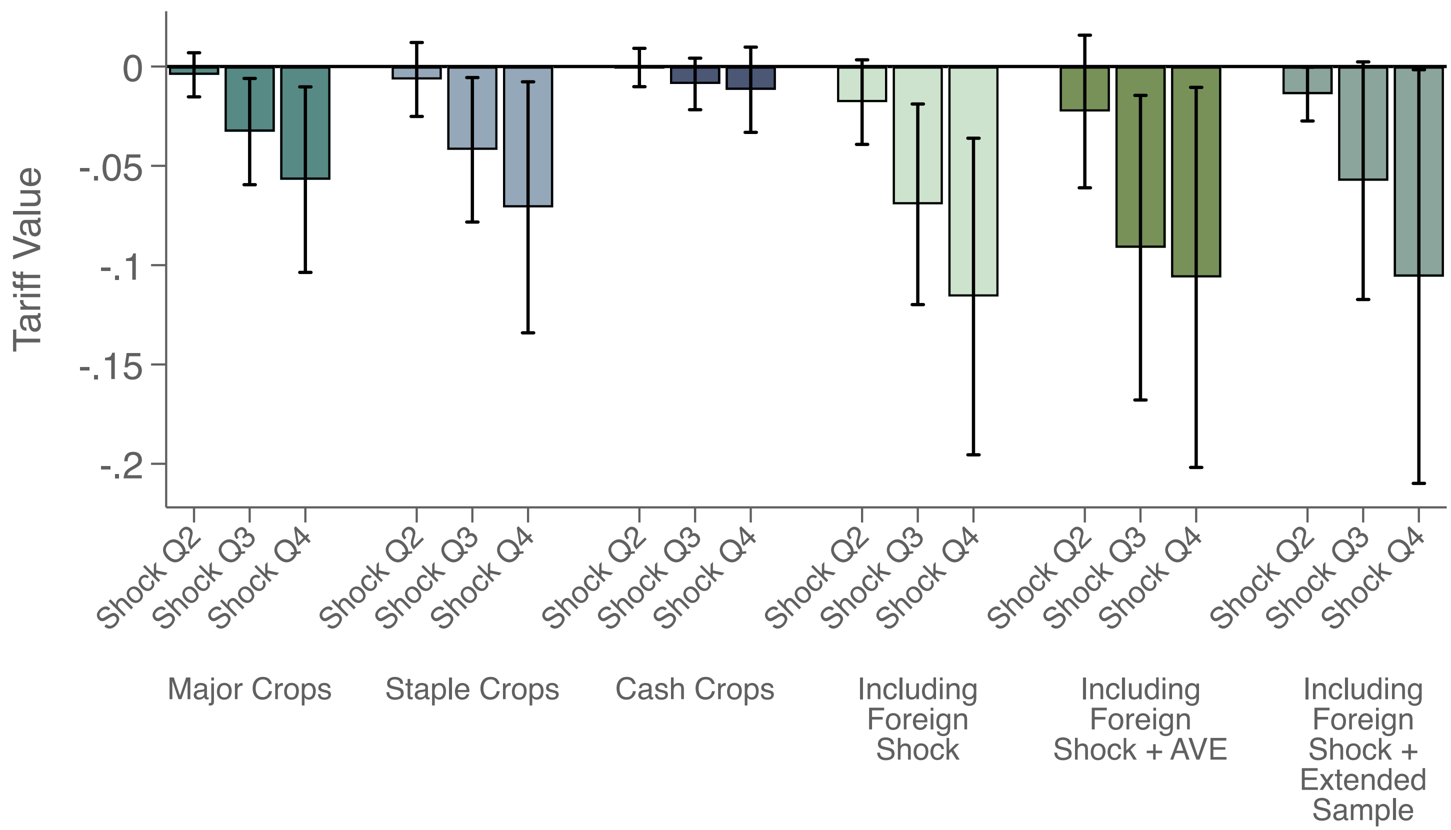
This figure displays the relationship between quartiles of extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each set of three bars corresponds to estimates from a single regression. The sample of crops included in each regression is noted below each set of bars. The 1990s are excluded from the sample. We report 90% confidence intervals.

Figure A.10: Extreme Heat and Agricultural Policy Excluding 2000s



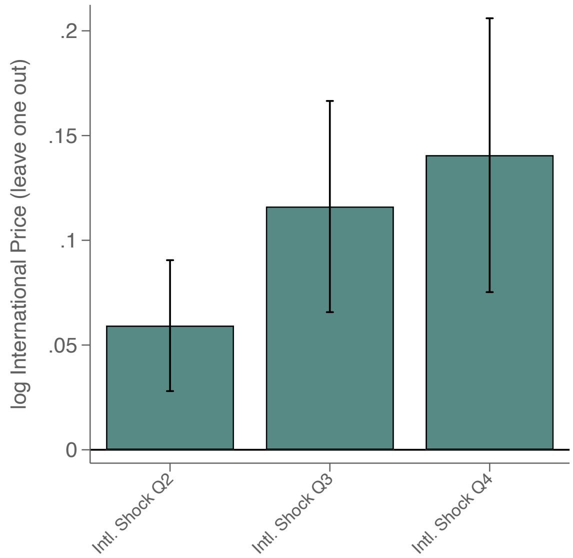
This figure displays the relationship between quartiles of extreme heat exposure and NRA. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each set of three bars corresponds to estimates from a single regression. The sample of crops included in each regression is noted below each set of bars. The 2000s are excluded from the sample. We report 90% confidence intervals.

Figure A.11: Extreme Heat and Agricultural Tariffs



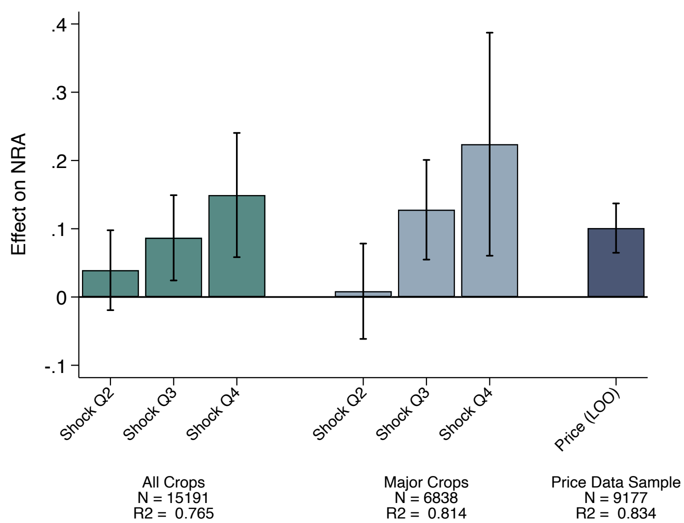
This figure displays the relationship between quartiles of extreme heat exposure and crop-specific tariffs measured using the World Bank's Trade Analysis Information System (TRAINS) database. The unit of observation is a country-crop-year and all possible two-way fixed effects are included. Each set of three bars corresponds to estimates from a single regression. The sample of crops included in each regression is noted below each set of bars. In the third through sixth set of bars, we also include quartiles of the import-weighted climate shock in the regression. In the fifth set of bars, we measure policy using the ad valorem equivalent, wherever possible. Following our main analysis, the baseline sample period ends in 2011 while in the sixth set of bars, we extend the sample to 2021. We report 90% confidence intervals.

Figure A.12: International Extreme Heat and Crop Prices



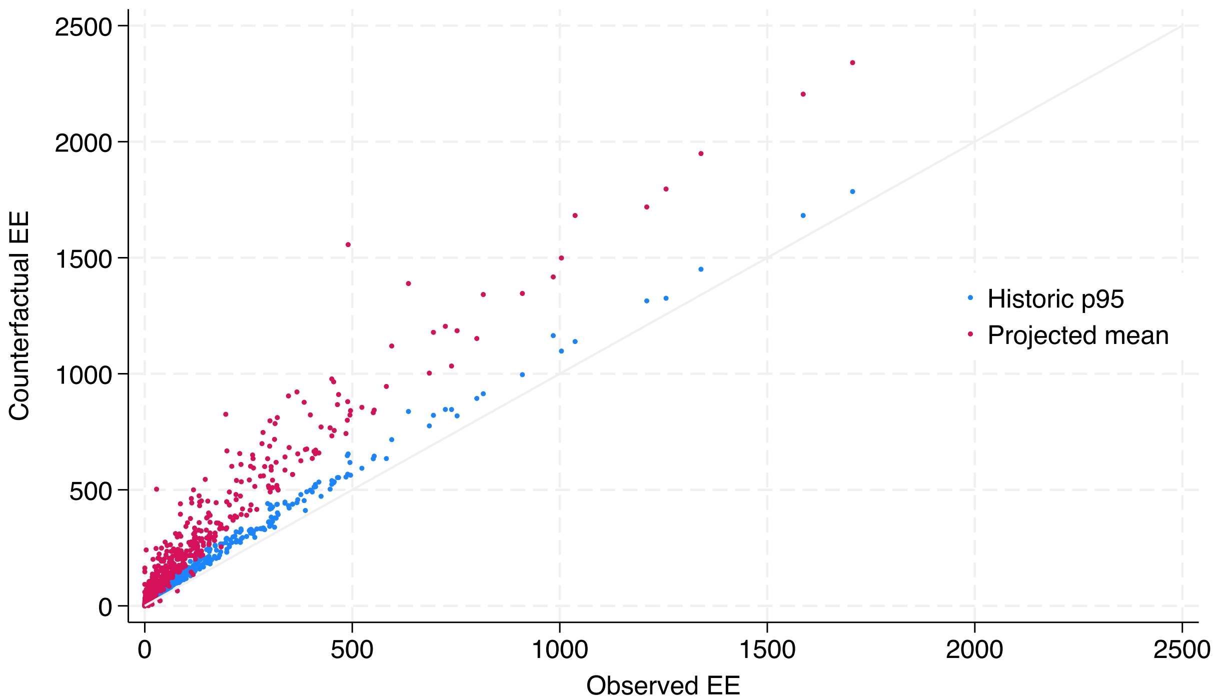
This figure displays the relationship between quartiles of foreign (import-weighted) extreme heat exposure and the (leave-one-out) production-weighted global price for each crop. The unit of observation is a country-crop-year and all country-year and crop-country fixed effects are both included. We report 90% confidence intervals.

Figure A.13: Agricultural Policy and Global Climate and Price Shocks



The first two panels of this figure display the relationship between agricultural policy quartiles of global (production-weighted, leave-one-out) extreme heat exposure. The third panel shows the relationship between agricultural policy and the global (production-weighted, leave-one-out) average price. The unit of observation is a country-crop-year and all country-year and crop-country fixed effects are both included. We report 90% confidence intervals.

Figure A.14: Extreme Heat Exposure in the Counterfactual Scenarios



This figure displays the relationship between the in-sample average extreme heat exposure for each crop-country pair and (i) the historic 95th percentile value (blue dots) and (ii) the projected average value for the 2090-20100 decade (red dots). The observed average extreme heat exposure is measured on the x-axis and the value of both sets of counterfactual measures of extreme heat exposure are measured on the y-axis.

Table A.1: Extreme Heat and Agricultural Policy Heterogeneity by Central Government Debt

	(1)	(2)	(3)	(4)
	Dependent Variable is NRA			
	Full Sample	Major Crops		
Q2 Extreme Heat Exposure	-0.0403	-0.0768	-0.151**	-0.0925*
	(0.0343)	(0.0515)	(0.0728)	(0.0548)
Q2 Extreme Heat Exposure	-0.0620	-0.122*	-0.323**	-0.142**
	(0.0514)	(0.0683)	(0.123)	(0.0623)
Q3 Extreme Heat Exposure	-0.163**	-0.399***	-0.614***	-0.434***
	(0.0712)	(0.146)	(0.180)	(0.150)
Q2 Extreme Heat Exposure x Central Government Debt	0.0366	-0.00497	0.0784	-0.00673
	(0.0510)	(0.0739)	(0.105)	(0.104)
Q2 Extreme Heat Exposure x Central Government Debt	0.110	0.0648	0.314*	0.0646
	(0.103)	(0.101)	(0.179)	(0.0977)
Q3 Extreme Heat Exposure x Central Government Debt	0.261**	0.327***	0.675***	0.370**
	(0.129)	(0.119)	(0.248)	(0.147)
Country x Year Fixed Effects	Yes	Yes	Yes	Yes
Crop x Year Fixed Effects	Yes	Yes	Yes	Yes
Country x Crop Fixed Effects	Yes	Yes	Yes	Yes
Country x Crop Fixed Effects x Central Government Debt	No	No	Yes	No
Interactions with change in debt	No	No	No	Yes
Observations	13,544	6,260	6,260	6,020
R-squared	0.861	0.862	0.840	0.867

Notes: The unit of observation is a country-crop-year. Central government debt is the dept to GDP ratio in the country year, as measured by the International Monetary Fund (IMF). The sample used in each specification is noted at the top of each column. Standard errors are double clustered by country and crop-year and *, **, and *** indicate significance at the 10%, 5%, and 1% levels.