Trade Policy and Food Security with Climate and Geopolitical Risk *

Levi Crews Ishan Nath Alice Schmitz Stephanie Stewart

April 11, 2025

Abstract

This paper evaluates the effects of trade openness on reliable access to affordable food. We start by showing that the transmission of extreme heat shocks to domestic food prices is weaker in countries with greater trade integration, even conditional on level of development, because productivity shocks are not highly correlated across space. On the other hand, importing countries face vulnerability to weather and policy shocks in countries from which they source. We show that global wheat prices diverged in the aftermath of the disruption to Ukrainian exports in 2022, with price increases strongly concentrated in countries importing directly from Ukraine. More broadly, importers face similarly disproportionate exposure to extreme heat shocks in source countries, suggesting that global agricultural markets are segmented and countries face adjustment costs to establishing new import sources. We plan to calibrate a quantitative trade model that rationalizes the patterns observed in the data and use it to compare the stability of food prices under varying levels of trade openness, as well as in policy scenarios that specifically subsidize import source diversification.

*Crews: UCLA, Department of Economics; Nath: Federal Reserve Bank of San Francisco; Schmitz: UC Berkeley, Department of Economics; Stewart: UC Davis, Department of Economics. Any views expressed in this paper are those of the authors and do not necessarily represent the views of the Federal Reserve System or its staff. Contact information: lgcrews@econ.ucla.edu, inath33@gmail.com, aschmitz@berkeley.edu, steph.stewart02@gmail.com.

1 Introduction

In 2023, the UN's Food and Agriculture Organization (FAO) reported that 2.3 billion people suffered from moderate to severe food insecurity, of whom nearly 800 million were defined as undernourished. These numbers have risen in recent years as extreme temperatures and other severe weather events have harmed harvests in many countries, and events such as Russia's war in Ukraine and multiple other wars have disrupted agricultural markets. Shocks to food supplies are likely to continue in coming decades - projections suggest that global warming could reduce global crop yields by up to 20% by later this century, with the possibility of even greater losses and volatility in vulnerable locations (Hultgren et al., 2022). For billions of people throughout the world, exposure to such shocks persistently threatens their secure access to sufficient nutrition.

The role of international trade in promoting food security is unresolved, and controversial. On one hand, the UN's Sustainable Development Goals target to end hunger by 2030 recommends that policymakers "prevent trade restrictions and distortions in world agricultural markets," a view echoed by the OECD's trade policy division.[1] These recommendations to promote free trade, however, focus heavily on preventing export restrictions and come alongside acknowledgments that reliance on imports exposes countries to excessive risk from global shocks and volatility.

The prevailing view among policymakers appears to be that food security is best achieved by promoting domestic production for domestic consumption. "Chinese people's rice bowls should mainly be filled by their own food" declared Chinese President Xi Jinping in 2019, voicing a view shared by many world leaders. In addition to China, Algeria, Bolivia, Ecuador, India, Mexico, Nepal, Nicaragua, Mali, Saudi Arabia, Senegal, and Venezuela are among a wide range of countries with national legislation promoting "food sovereignty," or a reliance on consumption from domestic sources of production.[2]

Prominent global policy leaders have made similar calls. In a recent essay entitled "Securing Africa's Food Sovereignty," the UN's Assistant Secretary General wrote in 2023 that "African countries must take steps to reverse their dependence on food im-

[1] See here for the UN Sustainable Development Goal website and here for the OECD's recommendations on food security.

[2] See this FAO technical report from 2016 for a summary of the policy debate about food self-sufficiency.

ports ... This would make Africa's food markets more resilient during global shocks."[3] Similarly, the UN Conference on Trade and Development's "Trade Agenda for the Right to Food" cautions that "excessive exposure to global markets and reliance on foreign supply increases risks and price volatility, which in turn compromises food security in many [developing] countries, with the stark human consequences it entails."[4] Are these policymakers right? Does trade integration lead to more or less exposure to volatility in agricultural markets, in a world with both environmental and geopolitical risks?

This paper empirically and theoretically investigates the relationship between trade openness and food security. We start by compiling a global dataset of food prices, agricultural production, bilateral trade flows, extreme heat exposure, agricultural policies, and geopolitical events across countries. We use the data to estimate the effects of environmental and geopolitical shocks on food prices, and show how their transmission to domestic and foreign countries varies with the level of trade integration. In the second part of the paper, we introduce a model of agricultural trade that rationalizes the empirical findings. In future drafts, we plan to use the model to conduct counterfactual simulations about the stability of food prices and supply under various agricultural trade policy regimes.

The paper has two key sets of empirical findings. First, we show that extreme heat shocks that harm agricultural productivity in panel regression estimates have smaller effects on domestic food prices in countries with greater levels of trade integration. Critically, we introduce a measure of trade integration based on the average number of partner countries from which a given country sources their agricultural commodities. We show that this measure of import source diversification strongly predicts a country's vulnerability to food price increases from domestic extreme weather, even conditional on a country's level of development. These results follow from the descriptive fact we document in our data that annual volatility in both weather and agricultural productivity decreases substantially at greater levels of geographic aggregation. Crop yields are much less volatile at the continent level than at the country level, and even less so at the global level, suggesting that diversifying consumption across sources from many locations can substantially reduce exposure to supply shortfalls and rising prices.

[3] See here for this essay, which was published by the Brookings Institution.
[4] See here for the full document.

We show that the mechanism through which import source diversification tempers the relationship between extreme heat and food prices is that countries with more import trade partners scale up imports more in response to adverse domestic shocks. The data also shows that conditional on the measure of import source diversification, the import share of agriculture is uncorrelated with the price effects of extreme heat. Countries with significant import shares of consumption from few partner countries do not show an ability to substitute toward imports or mitigate the price effects of local productivity shocks. In contrast, countries with low import shares that source from a wide variety of trade partners can increase imports substantially under unfavorable conditions and show little relationship between domestic weather and domestic food prices. Thus, the results suggest that general measures of integration may not capture the full food security implications of trade openness. The apparent importance of diversifying trade partners in the data suggests that importers may face meaningful delays or fixed costs to acquiring food from new sources when faced with domestic shortfalls, and that establishing many preexisting trade relationships can strengthen the capacity to respond to volatility.

The second key finding is that shocks to agricultural production transmit disproportionately to prices in the export destinations of the country in which the shock originates, further suggesting segmentation in global agricultural markets. We show this using event study estimates of the impact of the onset of the Russia-Ukraine war in February, 2022 on consumer prices for wheat and sunflower oil - Ukraine's major export crops - in Ukraine's export destination countries. We show that the prices of these two crops immediately and dramatically diverged in countries previously relying heavily on Ukrainian exports, with the price gap in the most intensive Ukraine importers reaching over 50% by the summer of 2022 and lasting through the end of the year. We also show no effect on the price of rice - a placebo crop not grown in Ukraine - in Ukrainian importers, suggesting that the wheat and sunflower oil price increases they faced were not due to an unrelated agricultural disruption that acted as an omitted variable. We interpret the estimates showing price divergence as evidence that importers from Ukraine could not shift their sourcing smoothly across countries, in which case the price pressures created by the war would have been distributed more evenly across the world.

To complement the event-study evidence from the Ukraine war, we show that extreme heat shocks similarly transmit disproportionately to export destinations. In particular, we

construct an index of each country's import-share-weighted exposure to foreign extreme heat in the trade partners from which they source their consumption. We show in panel regression estimates that extreme heat shocks in foreign trade partners raise domestic food prices, even controlling for year fixed effects that absorb global average food prices. This suggests that the mechanism observed in the aftermath of the Ukraine war - that productivity shocks transmit specifically to prices in the current set of consumer locations rather than being broadly felt in an integrated global market for agricultural commodities - also holds in a more systematic sense.

We rationalize these empirical findings in a general equilibrium model of global agricultural production, consumption, and trade under uncertainty. The key feature of the model is that countries face a fixed cost of adding import sources, and must make a choice about which countries to include in their set of source locations while facing uncertain conditions over a vector of productivity and policy shocks. Consistent with the evidence presented in the first part of the paper, new import sources cannot be added after the shocks are realized in a given period. Thus, the model can reproduce the patterns in which import source diversification is the key mechanism that mitigates the impact of domestic shocks on domestic prices, and in which both productivity and policy shocks transmit disproportionately to preexisting trade partner countries.

In future drafts of the paper, we plan to calibrate the model and use it to consider a range of counterfactual policy scenarios. In particular, we will compare the volatility of food prices and the risk of reduced food consumption in scenarios with varying levels of trade openness - starting with estimated levels of existing trade costs, which will be contrasted against scenarios with autarky, in which no country relies on imports, scenarios with hypothetical trade liberalizations that lower barriers to trade, and scenarios that specifically reduce the fixed cost of adding new import sources. We will compare the results of these counterfactuals with greater trade integration to the effects of alternative scenarios in which countries impose import tariffs and subsidize domestic production, in line with "food sovereignty" policies observed in many countries in practice.

This paper builds on several related literatures in agricultural, environmental, and international economics. The empirical work on extreme heat, agricultural markets, and trade integration builds on classic work on temperature, crop yields, and crop prices (e.g. Schlenker and Roberts, 2009; Roberts and Schlenker, 2013), and adds to a body of

evidence on the determinants of adaptation to extreme weather (Burke and Emerick, 2016; Hultgren et al., 2022; Moscona and Sastry, 2023). Another closely related literature considers the implications of international trade for climate change adaptation (Costinot, Donaldson and Smith, 2016; Gouel and Laborde, 2021; Conte, Desmet, Nagy and Rossi-Hansberg, 2021; Nath, 2025), but critically compares only across deterministic steady-states and does not consider exposure to volatility in yields and prices.

A small number of empirical papers consider the implications of trade openness in agricultural markets in the presence of shocks. Perhaps most notably, Burgess and Donaldson (2010) show that market integration through railroad access in India mitigates the impact of drought on famine intensity, and Jacks, O'Rourke and Williamson (2011) show in a long time series dating back to 1700 that global commodity prices are less volatile during periods of greater global market integration. The latter paper also documents that commodities show greater price volatility than manufactured goods, underscoring the importance of accounting for uncertainty in this setting. Relatedly, Dingel, Meng and Hsiang (2019) document the importance of accounting for the spatial correlation in productivity shocks when projecting climate change impacts across countries.

Two other groups of papers consider relevant topics pertaining to agricultural markets and trade. The first of these concerns the implications of uncertainty and trade openness for farmer crop choice, investment decisions, and productivity (Brooks and Donovan, 2020; Rivera-Padilla, 2020; Allen and Atkin, 2022); a set of mechanisms that is beyond the scope of our analysis. The second shows that agricultural *policy* is itself volatile, and that it responds endogenously to environmental shocks (Headey, 2011; Gouel and Jean, 2015; Gouel, 2016; Hsiao, Moscona and Sastry, 2024). We account for the findings from this literature in the shock structure we consider in the counterfactuals of this paper, in which climate, geopolitical, and policy risks covary and compound each other, rather than entering as independent shocks.

This paper also relates to more general literatures on uncertainty and trade, and on trade in the agricultural sector. On the first topic, Caselli, Koren, Lisicky and Tenreyro (2020) show that diversification through trade reduces exposure to individual country shocks, and that trade integration has reduced volatility in most countries over time. A number of other recent papers consider related issues in the context of supply chain risk, and evaluate the relative benefits of promoting domestic production or international

diversification across countries or locations within a country (Grossman, Helpman and Lhuillier, 2023; Leibovici and Santacreu, 2023; Castro-Vincenzi, Khanna, Morales and Pandalai-Nayar, 2024). This literature on trade and uncertainty dates back to original theory work from Helpman and Razin (1978) and Stiglitz and Newbery (1984). Finally, on agricultural trade more generally, it is worth noting papers on the importance of technology transfer (Farrokhi and Pellegrina, 2023) and on the broader causes and consequences of high agricultural trade barriers in low-income countries (Tombe, 2015; Porteous, 2019).

On the specific research question posed in this paper, two recent papers cover the most similar ground. Baptista, Spray and Unsal (2025) show that better market access across districts within Nepal is associated with muted effects of flooding on household food insecurity, and conclude that integration across space can mitigate exposure to shocks. In contrast, Adamopoulos and Leibovici (2024) find that trade integration is associated with greater food insecurity across countries, and that tariffs on imports and subsidies to domestic producers would reduce the variance of outcomes and raise consumption in the worst states of the world. Overall, however, the quantitative trade literature has made little progress on addressing the issue of food security. In the most recent Handbook of Agricultural Economics, Gaigné and Gouel (2022a) write that "since the above-mentioned literature on trade and uncertainty is econometric based and does not involve full-fledged trade models where uncertainty matters, **it is silent about the interactions between trade openness, volatility, and welfare.**" This paper aims to fill this critical gap.

The paper proceeds as follows. Section 2 describes the data sources and documents some motivating descriptive facts. Section 3 presents the central empirical results relating to extreme weather, geopolitical risk, trade integration, and market segmentation. Section 4 introduces the model, and Section 5 shows the strategy we use to calibrate it. Finally, Section 6 shows the effects of counterfactual policy scenarios, and Section 7 concludes.

2 Background

2.1 Data

We start by collecting globally comprehensive data on a wide range of relevant information: food prices, agricultural production, agricultural trade flows, agricultural policy, and weather exposure. This section briefly summarizes the sources of the primary data

used in the paper, with more details to follow when we present the descriptive facts in Section 2.2, the empirical estimates in Section 3, and the model calibration in Section 5.

We use two primary sources to measure consumer prices for food throughout the world. First, at the aggregate category level, the United Nations Food and Agricultural Organization (FAO) publishes a monthly food consumer price index for 203 countries and territories from 2000-2023. The FAO CPI compiles this dataset by combining information from a range of sources - the IMF, the United Nations Statistical Division, the OECD, the Central Bank of Western African States, and the Eastern Caribbean Central Bank, and directly from country statistical offices - in order to achieve essentially full coverage across the world. The food price index in each country is compared against the base year of 2015, such that price changes are comparable over time within country but not across countries.

Second, we observe crop-specific monthly food prices using data from the World Food Programme's (WFP) Vulnerability Analysis and Mapping (VAM) platform. This resource provides market-level commodity price data, generally at the monthly frequency, across 1920 active markets in 62 countries for a wide range of crop types and other agricultural commodities. The data is collected by representatives from WFP country offices using direct observation, interviews, and surveys, and includes whatever products are available in each local market rather than aiming for a consistent bundle across locations. Given that the WFP's focus is in low-income economies with the highest propensity for food security risks, the great majority of this data comes from Africa and South Asia.

Our data on agricultural productivity also comes from the FAO. This dataset contains harmonized annual statistics on crop production, acreage, and yield for 199 countries from 1961-2023. The data is primarily compiled from official national government statistics and responses to FAO questionnaires, but for completeness is supplemented with measures compiled by other national and international agencies and organizations. Yields for each crop are reported in kilograms per hectare. In Section 3.1, we compile an aggregate index of productivity across crops with different weight-to-value ratios by normalizing each crop's productivity by its long-term global average value.

Data on agricultural trade, which is central to our analysis, comes from the Base pour l'Analyse du Commercial International (BACI) database (Gaulier and Zignago, 2010). BACI reports a refined version of the trade data from the United Nations Comtrade Database. It covers over 200 countries from 1995-2022 for 5000 products listed at the

HS-6 digit classification, and reports both the dollar value and physical quantity of trade flows. In general, we aggregate bilateral trade flows to the HS 4-digit level (e.g. wheat) for analysis.

Finally, for temperature data to measure environmental shocks we use ERA-5 - the fifth generation reanalysis global climate and weather dataset from the European Centre for Medium-Range Weather Forecasts. The raw ERA-5 data provides hourly surface temperature estimates for a global grid of 0.25 by 0.25 degree resolution. We calculate killing degree days (KDD) on agricultural land by counting the number of degree-days above 29°C - a common threshold found in the literature beyond which increasing temperature harms crop yields (e.g. Schlenker and Roberts, 2009) - across each year in each grid cell. We then average KDD exposure across grid cells to the country level, weighting each grid cell by its share of cropped area in that country using data from Ramankutty et al. (2008). We execute these calculations using the open source programming package from Liddell et al. (2025).

2.2 Descriptive Facts

Fact 1: Volatility in Weather and Crop Yields Decreases with Geographic Aggregation

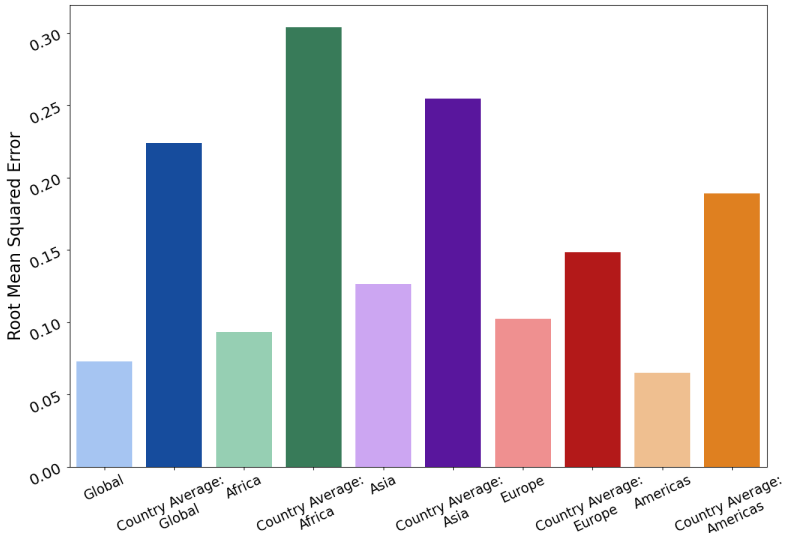
We start by using the raw data to show the *potential* for trade integration across the world to reduce volatility in food supply and prices. The idea we have in mind is that the benefits from diversification depend on the degree to which risk is uncorrelated across space. If agricultural productivity shocks have a large systematic component and tend to occur simultaneously across many countries, then trade integration that provides the option to substitute to foreign sourcing will provide little insurance against domestic shocks. In contrast, if shocks are largely idiosyncratic across space, then access to broad sourcing options will tend to smooth variability as the law of large numbers reduces the aggregate variation in supply shocks when averaging across many locations.

Figure 1 documents the year-to-year variability in crop yields (Panel A) and extreme heat (Panel B) at varying levels of geographic integration throughout the world. Specifically, we plot the root mean squared error of each variable relative to a linear trend, and compare the measure at the country, continent, and global level.

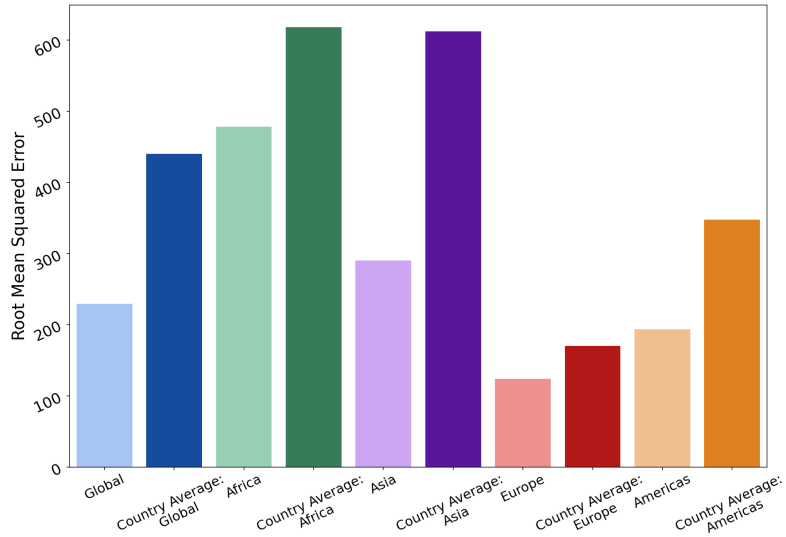
The results in Panel A show that detrended global crop yields display three times less year-to-year volatility than the country-level average. This suggests that, if annual

Figure 1: Potential for Geographic Diversification to Smooth Variability in Shocks

(a) Variability of Crop Yields by Geographic Aggregation



(b) Variability of Extreme Heat Exposure by Geographic Aggregation



Notes: Panel (a) plots the root mean squared error (RMSE) of crop yields relative to a linear trend of yields at the globe and continent level, as well as a continental average of the RMSE at the country level. Panel (b) plots the RMSE of extreme heat exposure relative to a linear trend for the same geographic aggregates. Data on crop yields is sourced from the FAO, and data on killing degree days is calculated using ERA-5 global climate data.

prices were to respond proportionately to yields, a fully integrated global agricultural market would be three times less volatile than the average country would be in autarky.

We interpret this result, which follows a similar finding in Gouel (2014) (Table 7.2), as evidence that trade integration could, in principle, substantially reduce the average country's exposure to volatility in food supplies.

While Figure 1a shows the potential benefits of diversification, it is worth noting that it does not imply that yield variation is uncorrelated across countries. If annual yield shocks were i.i.d. across countries, the law of large numbers would dictate that the standard deviation when averaging across countries would fall at the rate of the square root of the number of countries. Thus, with 200 countries, we would expect global variability to be about 14 times lower than country-level variability if agricultural productivity variation was entirely idiosyncratic and contained no systematic component. Given that the actual difference in country-level versus global variability is a factor of three rather than a factor of 14, the data suggests that yield shocks are strongly correlated across countries throughout the world. This correlation reduces, but does not eliminate, the potential for integrated global markets to provide insurance against domestic shocks.

Turning attention to the breakdown by continent in Figure 1a, the results show strong potential to reduce volatility by averaging yields even across countries within a continent. Unsurprisingly, countries in Africa and Asia (the green and purple bars) face the greatest exposure to year-to-year volatility in yields. This is both because these continents have a number of hot countries with large variation in annual exposure to harmful extreme temperature events (see Figure 1b), and because farmers in lower income countries may have a lower ability to mitigate the yield effects of extreme weather (we show direct evidence of this below in Section 3.1). Encouragingly, however, the continent-level measure of volatility is three times smaller than the country-level average in Africa, and twice as small in Asia. This indicates strong potential for trade integration to reduce food price volatility even if limited to nearby trade partners within the same continent.

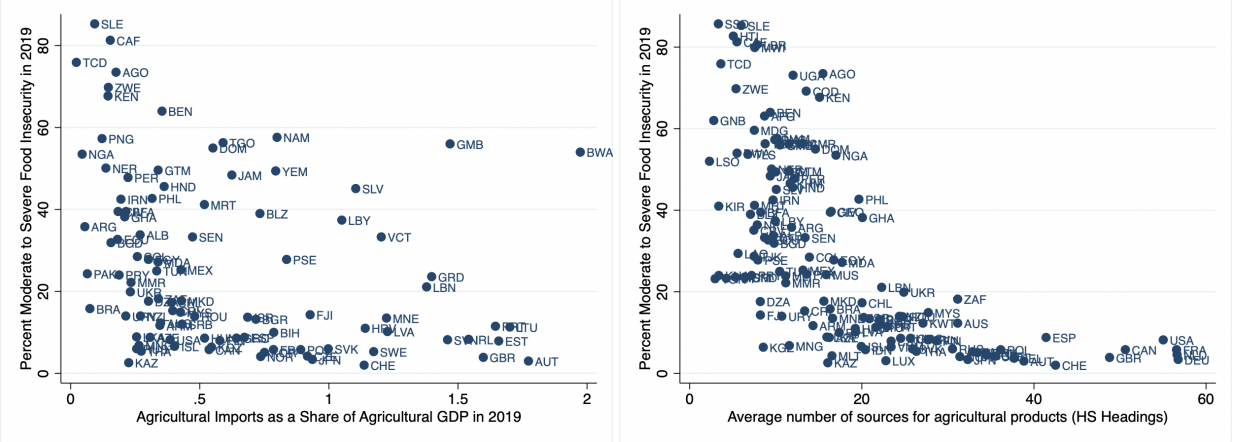
Fact 2: Agricultural Trade Integration is Correlated with Reduced Food Insecurity

Figure 2 shows the cross-sectional correlation between trade integration and food insecurity across countries throughout the world in 2019. We use the FAO's measure of "Moderate to Severe Food Insecurity," which is derived from a global survey they conduct annually, beginning in 2014, in partnership with the Gallup World Poll. The "Food Insecurity Experience Scale" survey module consists of eight questions measuring household access to food, frequency of skipping meals, and frequency of going hungry for

entire days.[5] Households experiencing moderate levels of food insecurity are characterized by an inability to consistently access healthy, balanced diets, and typically experience conditions that can be associated with micronutrient deficiency and diet-related health conditions. Severe levels of food insecurity are marked by household members regularly going entire days without eating, and are more likely to cause undernutrition and hunger.

Figure 2: Cross-Sectional Correlations Between Agricultural Trade and Food Insecurity

(a) Agricultural Import Shares (b) Agricultural Import Sources



Notes: Panel (a) plots each country's ratio of agricultural imports to agricultural GDP in 2019 against the percentage of citizens who experience moderate to severe food insecurity in 2019. Panel (b) plots each country's average number of import sources for agricultural products, averaged across HS-4 digit codes, against the same measure of food insecurity. Each country's average number of import sources for agricultural products is averaged across HS-4 digit code and calculated using BACI bilateral trade flows. Agricultural import shares are calculated using the BACI data on total agricultural imports and UNSD data on agricultural gross value added as well as a gross output deflator to calculate imports in value added terms, rather than the gross output terms in which they are reported.

We show cross-country correlations of food insecurity with two measures of trade integration. First, in Figure 2a, we measure trade integration using a standard variable - the import share of agricultural production. We calculate import share as the sum of agricultural imports from all sources in a given country-year, divided by agricultural GDP.[6] This represents a country's overall reliance on imports, relative to domestic production, for agriculture.

[5]See here for the full list of survey questions, and for more information.

[6]The ideal measure of agricultural import share would use agricultural consumption, rather than production, as the denominator, but we lack data on an aggregate measure of agricultural consumption that is comparable across crops.

The results in 2a show a moderately strong negative correlation between agricultural import shares and reported levels of food insecurity. With some exceptions, the countries in the world with the greatest share of their populations experiencing food insecurity, which range as high as 40% to 80% in some places, typically import little food relative to domestic production. We interpret this as evidence that food "self-sufficiency" - or the ability to rely on domestic production, as frequently referenced by policymakers - is not a sufficient condition for achieving food security. Many countries in the world that produce most of their own food at home also suffer greatly from food insecurity.

The second measure of agricultural trade captures the degree to which a country's agricultural imports are diversified across trade partners. We calculate this measure by counting the number of unique source countries that provide each country's imports at the HS-4 digit level, and then averaging across HS-4 digit codes in the agricultural sector.[7] For agriculture, HS-4 codes refer to types of crops, such as wheat or maize, but do not differentiate across varieties of a crop. Thus, our measure captures source diversification at the crop level. If a given country were to import each commodity from a different singular trade partner or from one consistent origin country, the average number of import sources would be counted as one either way. A country is diversified by this measure only if it obtains a given commodity (e.g. wheat) from many source countries.

The results in Figure 2b show a strong cross-sectional correlation between food insecurity and agricultural import source diversification. The R-squared for this relationship is 0.40, which represents a markedly stronger correlation than that of agricultural import shares in Panel A, which has an R-squared of 0.10. Among countries with at least 40% of the population experiencing food insecurity, not a single one is above the global median of agricultural source diversification, and a substantial number of them have five or fewer import sources per agricultural product. The converse is also true. Among countries with more than 20 import sources per product, none of them have a food insecurity share above 20% of the population.

In sum, reliance on domestic production is not associated with high levels of food security globally, and in fact the opposite is true. There is also an especially strong negative correlation between food insecurity and trade integration as captured by our measure of import source diversification, a mechanism that we emphasize throughout this paper.

[7] In line with Nath (2025), we define agriculture to include HS 1992 2-digit product chapters 1-24.

We note, of course, that these correlations are only suggestive, and that overall levels of poverty are an important omitted variable in this graph given the widely documented evidence that low-income countries are especially closed to agricultural trade (Tombe, 2015). Further, in this paper we are interested not primarily in levels of deprivation, but rather in vulnerability to volatility created by environmental and geopolitical shocks. We investigate the role of such shocks, and how their effects vary with trade integration, below in Section 3.

Fact 3: Trade Policy Risk is Endogenous to Agricultural Market Risk

It is well known that the recent history of global food price increases has been marked by the simultaneous imposition of widespread agricultural trade barriers. Anecdotally, the time series pattern is clear. The two major increases in global food price spikes over the past two decades occurred in 2008-09, and during COVID and the Russia-Ukraine war in 2020-23. The data shows that 36 countries imposed export restrictions in the former crisis, and another 34 followed during the latter.[8] Hsiao, Moscona and Sastry (2024) provide evidence that this relationship is causal - exposure to extreme heat makes countries more likely to impose trade restrictions.

The pattern in which global trade restrictions and global food prices mirror each other over time makes clear that climate and geopolitical risk covary in important ways, and cannot be treated as independent. Environmental risk is correlated across countries, policy risk is correlated across countries, and the two types of risk are correlated with each other. Thus, policymakers interested in shielding their citizens from volatility in agricultural markets must consider the joint distribution of environmental and geopolitical risks, and the ways in which they reinforce each other. We aim to take these patterns into account in the counterfactuals we consider in Section 6.

[8]See data from the International Food Policy Research Institute and the World Bank here and here.

3 Empirical Results

3.1 Domestic weather shocks, food prices, and trade integration

We start by examining how the effects of extreme weather on food prices at the national level vary with trade integration. To do so, we estimate the following panel regression at the country-year level:

$$y_{it} = \beta_1 KDD_{it} + \beta_2 GDD_{it} + \gamma_1 ImportShare_{it-1} \times KDD_{it} + \gamma_2 ImportSources_{it-1} \times KDD_{it} + \gamma_3 GDPpc_{it-1} \times KDD_{it} + \delta_i + \delta_t + \epsilon_{it} \quad (1)$$

In the initial specification the dependent variable y_{it} refers to the FAO's food consumer price index. Recall that killing degree days (KDD) measure country-level exposure to extreme heat on cropland, and growing degree days (GDD) measure exposure to moderate warm temperatures. We interact our measure of extreme heat with two measures of trade integration, and with a country's GDP per capita. We use lagged measures of variables representing trade integration and level of development to examine heterogeneity, since these are also themselves a function of extreme heat exposure in year t.

The variables import share and import sources refer to the two distinct measures of agricultural trade introduced in Section 2.2 and shown in Figure 2. Import shares measure the relative prevalence of total agricultural imports versus domestic production in a given country. Import sources measure the average diversification across different import source country trade partners for agricultural products in a given country.

Table 1 shows the results from estimating Equation 1, starting with only the uninteracted coefficients on KDD and GDD in Column 1 and introducing the interaction terms one at a time. For interpretation purposes, in all subsequent columns beyond Column 1 the table shows the KDD coefficient evaluated at the median value of all included interaction terms such that the effect can be interpreted as the effects of KDD in an average country throughout the table. The results in Column 1 show the intuitive effect that domestic extreme heat shocks raise domestic consumer food prices. The magnitude of the coefficient implies that 100 KDD would raise the consumer price index by about 12% in the year of the shock. For context, 100 KDD is approximately a two standard deviation heat shock in many hotter agricultural economies in sub-Saharan Africa and South Asia.

Table 1: Extreme Heat Effects on Food Prices - Heterogeneity with Trade Integration

	Food CPI					
	(1)	(2)	(3)	(4)	(5)	(6)
Killing Degree Days (KDD)	0.1183***	0.0859*	0.1376***	0.1293**	0.0923***	0.1238***
	(4.11)	(2.07)	(3.72)	(2.63)	(5.08)	(3.32)
Growing Degree Days (GDD)	-0.0009	-0.0038	-0.0017	-0.0064	0.0031	-0.0023
	(-0.12)	(-0.55)	(-0.25)	(-0.88)	(0.51)	(-0.36)
KDD × Agricultural Import Shares		-0.0043**		0.0013		0.0006
		(-2.22)		(1.40)		(0.51)
KDD × Average # of Import Sources			-0.0030***	-0.0030***		-0.0021**
			(-3.10)	(-2.82)		(-2.39)
KDD × Log GDP per capita					-0.0639**	-0.0469**
					(-2.51)	(-2.14)
N	4328	3404	4303	3404	4279	3378

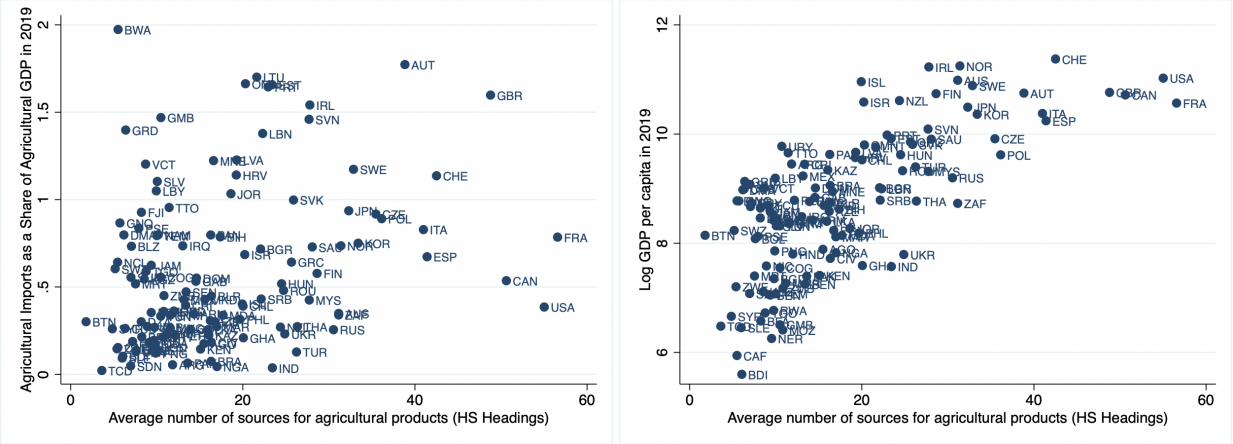
Notes: t-statistics in parentheses. Results come from estimating Equation 1 with a food consumer price index as the dependent variable. Column 1 include only the uninteracted terms, and the following columns add the interaction terms one at a time. GDD measure 24 hour increases of 1°C between 0 and 29°C, typically helpful for crops, and KDD contain the corresponding measure for increases above 29°C, typically harmful for crops. All equations include country and year fixed effects. Import sources are calculated using BACI data. Killing degree days and growing degree days are derived from ERA-5. GDP per capita is taken from the World Development Indicators. Agricultural import shares are calculated as in Figure 2a.

Columns 2 and 3 of Table 1 show how the effects of KDD on food prices vary with the two measures of trade integration, introduced one at a time. The results show that the effects of KDD on food prices are significantly smaller both in countries with higher import penetration rates and with more import source diversification. This result is also intuitive - domestic shocks have smaller effects on domestic prices when a country is more open to trade.

Which measure of trade integration matters more for mediating the effects of extreme heat on prices? In Column 4 we include both interaction terms in the same regression. Figure 3a shows that while these measures of trade integration are positively correlated in the data with an R-squared of 0.088, there remains substantial variation in import source

Figure 3: Variation in Agricultural Import Source Diversification

(a) Correlation with Agricultural Import Shares (b) Correlation with GDP Per Capita



Notes: Panel (a) plots each country's average number of import sources for agricultural products, averaged across HS-4 digit codes, against the ratio of agricultural imports to agricultural GDP in 2019. Panel (b) plots the same measure of import sources against the logarithm of GDP per capita in 2019. Average number of import sources are calculated using bilateral flows from the BACI data. Agricultural import shares are calculated using the BACI data and UNSD data on agricultural GDP. GDP per capita is sourced from the World Development Indicators.

diversification conditional on import share. Some countries, such as Belize or Botswana, have large import shares concentrated among few sources, while others, such as India or Turkey, average over 20 partner countries for each agricultural commodity despite low aggregate import shares. This variation allows us to separately estimate how each measure of trade integration correlates with the prices effects of extreme heat.

The results in Column 4 of Table 1 show that import source diversification is the key measure of trade integration associated with reduced effects of KDD on prices. The coefficient on agricultural import shares in this specification is close to zero, and has the opposite sign as in Column 2 that does not control for source diversification. In contrast, controlling for import share has no impact at all on the interaction coefficient for import source diversification, which continues to strongly associate with a weakened effect of KDD on yields. To put the magnitude in context, the estimates imply that a country that averages over 50 import sources per commodity, which would be towards the top of the range of the import source diversification measure shown in Figure 3, would have virtually no effect of KDD on prices.

Columns 5 and 6 of Table 1 verify that the correlation between trade integration and the KDD-price relationship is not driven by the omitted variable of a country's level of development. Column 5 of Table 1 shows that higher GDP per capita is strongly associated with a weaker effect of KDD on prices. Given that Figure 3b shows a strong correlation across countries between GDP per capita and import source diversification, this suggests that the results in Column 4 could be driven by the correlation between import source diversification and country income. However, Column 6 shows that this is not the case. The coefficient on import source diversification is slightly smaller when controlling separately for the GDP per capita interaction term, but it remains economically and statistically significant.

Overall, the estimates in Table 1 show that countries with more import source diversification have a substantially weaker relationship between extreme heat and food prices. Conditional on this measure of source diversification, an alternative measure of trade integration based on agricultural import shares is uncorrelated with the effects of KDD on prices. Critically, while we do not have full causal identification for the interaction terms in Equation 1, we do show that the relationship between import source diversification and reduced price effects of heat shocks holds when controlling for the key omitted variable of GDP per capita.

Mechanisms

In Table 2 we examine the mechanisms through which import source diversification affects the relationship between extreme heat and food prices. To do so, we re-estimate the specification from Equation 1 with the log of agricultural imports as the dependent variable in Panel A, and an index of crop yields as the dependent variable in Panel B.

The results in Panel A of Table 2 show that countries with greater source diversification scale up their agricultural imports more in response to adverse weather shocks. Column 1 displays the main effect of KDD on agricultural imports. The estimates show that countries substantially raise their agricultural imports in response to extreme heat, with approximately a 12% increase for every 100 KDD.[9] Columns 2 and 3 show that both measures of trade integration are correlated with a stronger import response to extreme heat when entering the regression individually, but that only import source diversification

[9] As in Table 1, we evaluate the KDD coefficient at the median of all the interaction terms in Columns 2-6 such that the coefficient can be interpreted as the effect of KDD in the average country.

Table 2: Extreme Heat Effects on Agricultural Imports and Crop Yields Heterogeneity with Trade Integration

	Panel A: Log Agricultural Imports					
	(1)	(2)	(3)	(4)	(5)	(6)
Killing Degree Days (KDD)	0.1185***	0.0806***	0.0674***	0.0308*	0.1158***	0.0349
	(5.88)	(3.91)	(4.29)	(1.94)	(6.71)	(1.68)
Growing Degree Days (GDD)	-0.0048	-0.0010	-0.0017	0.0023	-0.0049	0.0017
	(-0.92)	(-0.19)	(-0.32)	(0.43)	(-0.95)	(0.34)
KDD × Agricultural Import Shares		0.0066**		-0.0022		-0.0015
		(2.65)		(-1.15)		(-0.92)
KDD × Average # of Import Sources			0.0028***	0.0034***		0.0027***
			(7.85)	(5.71)		(4.37)
KDD × Log GDP per capita					0.0746***	0.0636***
					(6.63)	(6.93)
N	5247	3859	5057	3859	5150	3830
	Panel B: Crop Yield Index					
	(1)	(2)	(3)	(4)	(5)	(6)
Killing Degree Days (KDD)	-0.0492***	-0.0610***	-0.0677***	-0.0866***	-0.0483***	-0.0874***
	(-8.27)	(-5.37)	(-4.54)	(-4.50)	(-7.00)	(-4.33)
Growing Degree Days (GDD)	0.0049	0.0020	0.0063	0.0037	0.0052	0.0035
	(0.80)	(0.35)	(0.96)	(0.62)	(0.81)	(0.59)
KDD × Agricultural Import Shares		-0.0005		-0.0051**		-0.0050**
		(-0.28)		(-2.38)		(-2.37)
KDD × Average # of Import Sources			0.0012***	0.0017***		0.0017***
			(2.84)	(3.36)		(3.06)
KDD × Log GDP per capita					0.0198**	0.0032
					(2.22)	(0.38)
N	5215	3833	4977	3833	5090	3805

Notes: t-statistics in parentheses. Results in Panel (a) come from estimating Equation 1 with the logarithm of agricultural imports as the dependent variable. Panel (b) estimates Equation 1 with a crop yield index as the dependent variable. The crop yield index normalizes across crops with different weight-to-value ratios by using each crop's yield z-score relative to all country-years observed for that crop, and then weights across crops within a country-year by production value. GDD measure 24 hour increases of 1°C between 0 and 29°C, typically helpful for crops, and KDD contain the corresponding measure for increases above 29°C, typically harmful for crops. All equations include country and year fixed effects. Crop yield data is sourced from the FAO. Log agricultural imports and average number of import sources are calculated using BACI data. Killing degree days and growing degree days are derived from ERA-5. GDP per capita is taken from the World Development Indicators. Agricultural import shares are calculated as in Figure 2a.

shows an association when both enter the regression as separate interaction terms. To put the magnitudes in context, the estimates imply that the highest scoring countries in the measure of source diversification increase agricultural imports over five times more for the same heat shock, in percentage terms, than the least diversified ones.

Column 5 of Table 2 Panel A shows that agricultural imports are much more responsive to extreme heat in richer countries. Between Column 5 and Column 6, the coefficients on the interaction term for GDP per capita imply that the world's richest countries would scale up agricultural imports by roughly 20 to 30 percentage points more than the world's poorest countries if faced with a 100 KDD heat shock. Most importantly, Column 6 shows that the correlation between import source diversification and the import response to extreme heat remains very similar even when controlling for GDP per capita. Conditional on level of development and agricultural import share, countries that import from more partners show a much greater ability to increase agricultural imports in response to adverse domestic shocks.

Panel B of Table 2 shows the effects of extreme heat on a country-level index of crop yields. The index normalizes across crops with different weight-to-value ratios by using each crop's yield z-score relative to all country-years observed for that crop, and then weights across crops within a country-year by production value. Column 1 verifies the long established result in the literature (Schlenker and Roberts, 2009, e.g.) that our measure of extreme heat has a large effect on crop yields. Column 5 further confirms the previous finding that farmers in richer places are more adapted and experience smaller productivity losses from heat shocks (Hultgren et al., 2022, e.g.). The interaction terms on the measures of trade integration in Columns 4 and 6, however, are of opposing sign and do not show a clear pattern. While we might in principle expect some scope for trade integrated countries to have access to better adaptive technologies (see, for example, Farrokhi and Pellegrina (2023)), the results suggest that this is not a key mechanism driving the effects seen in Table 1.

Overall, we interpret the evidence in Table 2 as showing that the key mechanism that allows countries with more import source diversification to alleviate the price effects of extreme heat is that these countries are more able to scale up their imports in response to adverse shocks. These patterns are consistent with importers facing barriers to switching across source countries, such as fixed costs or regulatory constraints. In the absence of

such frictions, we would not expect to see a country's ability to increase their imports in the short run depend on the preexisting number of partner countries from which they source, as the results suggest. In the next section we present further evidence of market segmentation consistent with countries facing obstacles to reallocating across import sources.

3.2 Segmentation in global agricultural markets

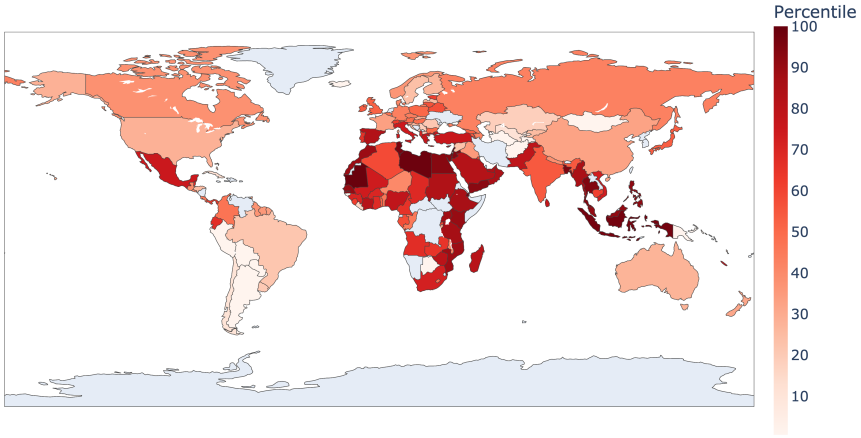
In this section we examine the effects of the 2022 onset of the Russia-Ukraine war on the price of key Ukrainian export crops in other countries throughout the world. Ukraine is a major global producer of several important crops. In the five years prior to 2022, Ukraine accounted for about 7% of the world's wheat exports, 37% of the sunflower oil, and 11% of the maize. The known timing of this large exogenous shock to agricultural production and trade in a major global exporter provides an opportunity to evaluate the degree to which global agricultural markets are integrated. If importers can substitute flexibly across source countries, the increase in prices caused by the shock to global supply should be broadly similar across countries, regardless of a given destination's initial reliance on Ukrainian exports. If markets are segmented, however, and countries face barriers or delays in switching between import sources, we might expect price increases to concentrate disproportionately in Ukrainian export destinations.

As background for the analysis that follows, we note that Russia first invaded Ukraine on February 24th, 2022. Starting immediately after, Ukrainian sea ports were virtually completely cut off from global markets due to a combination of infrastructure damage, security risks, and ongoing warfare. As a result, their exports of key crops, such as wheat and corn, fell by over 90% over the following five months according to data from the USDA.[10] This sharp decline in exports lasted until July of 2022, when Russia and Ukraine signed the Black Sea agreement that enabled safe passage of Ukrainian grain exports through three major ports. By the fall of 2022, monthly Ukrainian exports of key crops were restored to levels close to their historical average, though far below the levels necessary to compensate for the missing supply from the spring. Overall, the Ukrainian wheat harvest for 2022 fell by 38% relative to the previous year due to reductions in both area planted and farm labor available during the war.

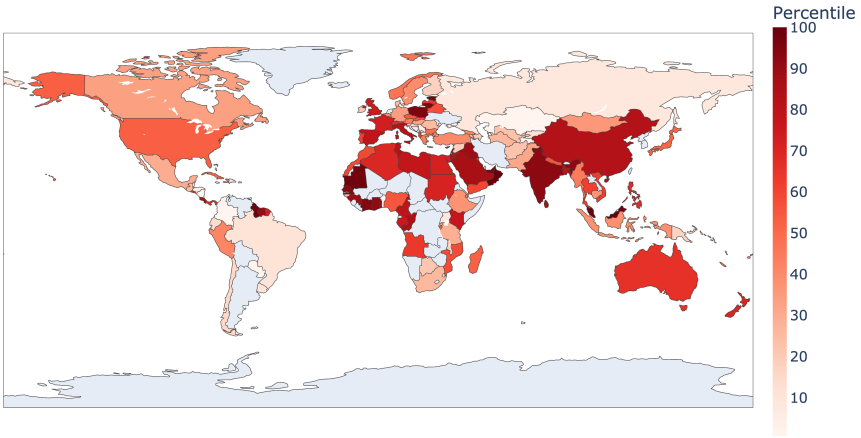
[10] See here for the January 2023 Wheat Outlook from the USDA Research Service.

Figure 4: Geography of Importers from Ukraine

(a) Wheat Importers from Ukraine by Decile of Consumption Share



(b) Sunflower Oil Importers from Ukraine by Decile of Consumption Share



Notes: Panel (a) plots the percentile (across all countries) of each country's ratio of wheat imports from Ukraine to their total wheat consumption. Panel (b) plots the same percentile for sunflower oil. The ratio is constructed using BACI trade flow data and FAO consumption data.

The decline in Ukrainian wheat exports in 2022 was especially severe for their usual primary destinations. Given the shock to port infrastructure, the wheat that Ukraine did produce was largely shipped via rail to Romania, Poland, Hungary, and other members of the European Union. EU imports comprised only 4.1% of Ukrainian wheat from 2017-2021, but nearly half in 2022. In contrast, countries importing wheat through Ukrainian sea routes were especially exposed to the drop in supply. Egypt, Indonesia, the Philippines, and Bangladesh accounted for nearly 40% of Ukrainian wheat exports from 2017-

2021, but only 5% of the reduced quantities shipped in 2022. Figure 4 shows the full range of reliance on imports of Ukrainian wheat and sunflower oil, as a share of overall consumption of each crop.

We test the hypothesis that the onset of the Ukraine war caused prices to diverge in Ukraine importers using the following event study specification:

$$y_{it} = \delta_i + \gamma_t + \beta_t \times \overline{UkraineShare_i} \times \mathbf{1}\{\text{month} = \text{t}\} + \epsilon_{it} \tag{2}$$

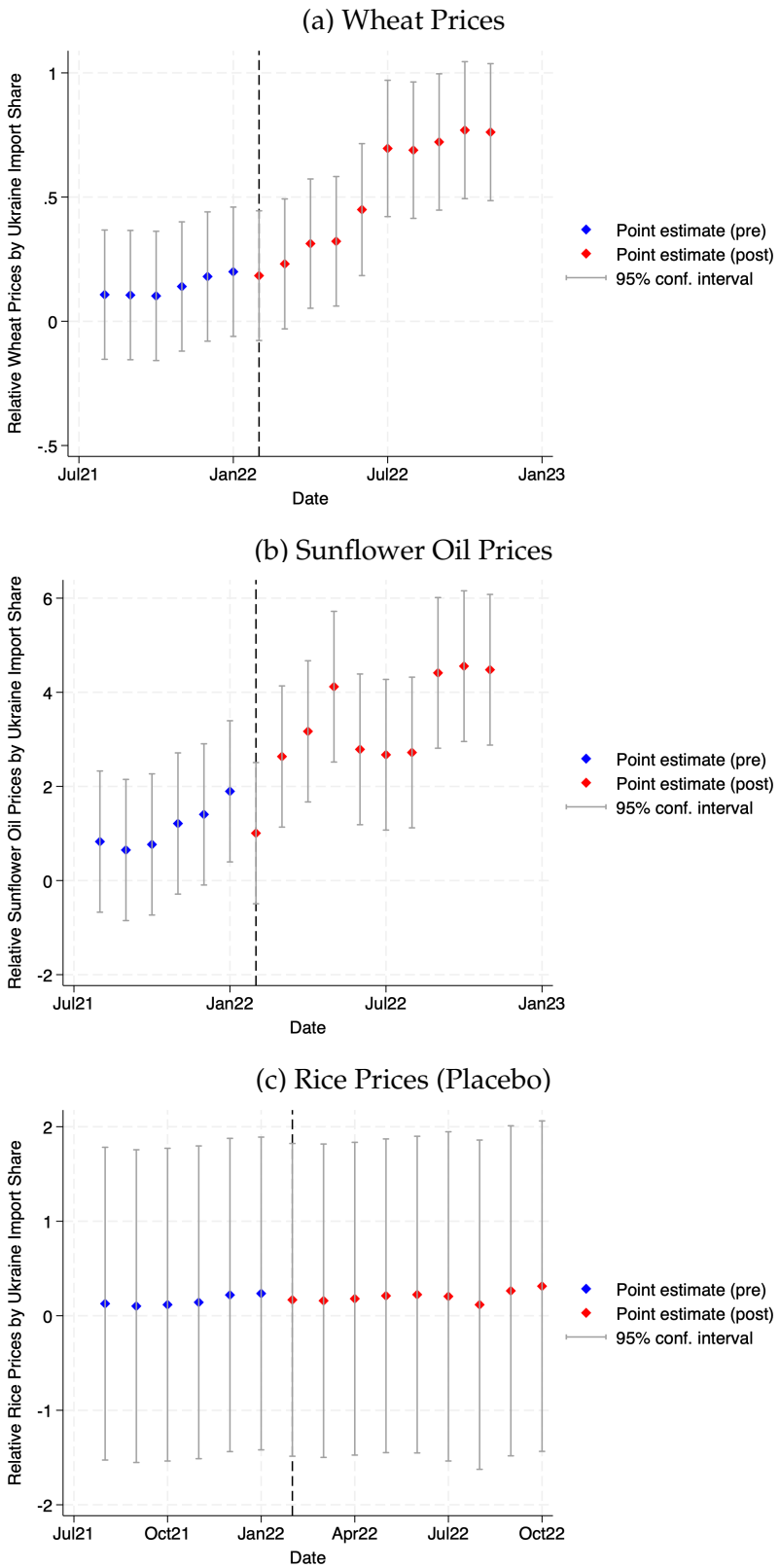
The dependent variable in Equation 2 is monthly average prices in country i in year t using data from the World Food Program. The WFP collects data on commodity level prices from local consumer markets located throughout each of 62 developing countries, which we average to the country level.[11] We use this data because it is the most globally comprehensive available source of monthly local crop prices, and because it measures prices at the point of sale to consumers that is most relevant for affordability and food security. We define the Ukraine share variable as the ratio of each country's imports from Ukraine to their total crop consumption, as measured by the FAO, averaged over the period from 2017-2021. Note that we estimate Equation 2 for wheat and sunflower oil, but not for maize - Ukraine's other major export crop - because the WFP data does not cover the European Union or China, which account for over half of Ukraine's maize exports.

Figure 5a shows the results from estimating Equation 2 for wheat prices. The graph shows that relative wheat prices in countries exposed to Ukrainian imports began to rise immediately after the onset of the war. The price divergence peaked by July of 2022, and did not begin reverting at all by the end of the year (WFP price data for 2023 are not yet available). To interpret the magnitude of the coefficients, Appendix Figure A-1 shows estimates from a binary version of the difference-in-difference specification from Equation 2 that compares prices in the top quartile of Ukraine importers relative to all other countries. The results there show that wheat prices in the most Ukraine-dependent countries rose by over 50% by the fall of 2022.

Figure 5b shows a similar effect on the price of sunflower oil in countries importing from Ukraine. To interpret magnitudes, Figure A-1b shows that the price divergence for sunflower oil also reached 50% in the countries most exposed to the fall in Ukrainian

[11] Of the 62 countries in the WFP data, 46 of them have the necessary coverage of crop type and time period to be included in the regression.

Figure 5: Differential Impact of Ukraine War on Food Prices in Direct Importers



Notes: Panel (a) plots coefficients for an event study regressing monthly wheat prices on a month indicator interacted with the ratio of a country's wheat imports from Ukraine to their total wheat consumption. Months displayed are those preceding and following Russia's invasion of Ukraine in February 2022. Panel (b) shows the same specification with sunflower oil prices as the dependent variable and exposure to Ukrainian sunflower oil imports. Panel (c) serves as our placebo using rice prices as the dependent variable and exposure to Ukrainian wheat imports. All regressions include month and country fixed effects. Outcome variable data comes from WFP consumer price data. Exposure to Ukrainian imports is constructed using crop-level BACI trade flows and FAO consumption data.

imports. Note that the set of countries importing sunflower oil from Ukraine shown in Figure 4b differs somewhat from the wheat importers shown in Figure 4a, which strengthens the evidence that exposure to Ukrainian imports, rather than an omitted variable occurring at the country level, caused the observed price divergence in 2022.

To further rule out omitted variable bias, Figure 5c shows the event study estimates from Equation 2 for rice, a crop Ukraine does *not* produce and export. In this specification, we weight countries using their consumption share of Ukrainian *wheat* imports, and show that there was no differential change in *rice* prices in Ukraine's primary wheat importers. This evidence adds additional confirmation that the observed pattern of prices was caused by exposure to the decline in Ukraine's exports, rather than unrelated developments in the agricultural markets of Ukraine's import sources. Taken together, the estimates in Figure 5 can be taken as a difference-in-difference-in-differences that exploits country-level variation in Ukrainian import exposure, crop-level variation in Ukrainian import exposure, and the exogenous timing of the start of the war.

We interpret the evidence in Figure 5 as consistent with market segmentation. If countries could switch import sources seamlessly, Ukrainian destination countries looking to fill their supply shortfalls would have bid up prices for wheat produced in other locations, and the price increases would be observed more uniformly across space. Instead, somewhat remarkably, the raw time-series of wheat prices shows no change at all in countries with the least import dependence on Ukraine.

To provide more systematic evidence of market segmentation beyond the Ukraine war, we next examine whether extreme heat shocks also propagate differentially to food prices in export destinations. To do so, we start by constructing a country-level index of exposure to source country KDD. We construct the index as follows. For each importer, we calculate the average number of KDDs across all source countries, weighted by the value of agricultural trade flows from the respective source countries in the previous year. Values from the prior year are used as weights to avoid endogeneity issues arising from the effects of KDD on trade flows. The measure of source country KDDs is defined as follows:

$$\overline{SourceKDD_{it}} = \frac{\sum_j AgImports_{ijt-1} \times KDD_{jt}}{TotalAgImports_{it-1}} \tag{3}$$

Table 3: Effects of Source Country Extreme Heat on Domestic Agricultural Markets

	(1) Food CPI	(2) Food CPI	(3) Crop Yield Index	(4) Log Agricultural Imports
Average Import Source Country KDD	0.0051*	0.0041*	-0.0006**	0.0080***
	(2.13)	(1.89)	(-2.09)	(3.53)
Average Import Source Country GDD	-0.0001	-0.0001	-0.0002***	-0.0001
	(-0.90)	(-0.55)	(-3.87)	(-0.16)
Killing Degree Days (KDD)		0.0630***	-0.0388***	0.0487***
		(2.88)	(-7.22)	(2.83)
Growing Degree Days (GDD)		0.0034	0.0049	0.0015
		(0.44)	(0.80)	(0.38)
N	4674	4303	4976	5056

Notes: t-statistics in parentheses. Results come from estimating a panel regression with year and country fixed effects. The dependent variables are the FAO's Food CPI (Columns 1 and 2), an index for crop yields (Column 3), and log agricultural imports (Column 4). The crop yield index normalizes across crops with different weight-to-value ratios by using each crop's yield z-score relative to all country-years observed for that crop, and then weights across crops within a country-year by production value. GDD measure 24 hour increases of 1°C between 0 and 29°C, typically helpful for crops, and KDD contain the corresponding measure for increases above 29°C, typically harmful for crops. Average import source country KDD and GDD are calculated using Equation 3. Killing degree days and growing degree days are derived from ERA-5 global temperature data. Bilateral agricultural flows used to weight source country KDD and GDD, as well as to calculate log agricultural imports, are from BACI. Food CPI and crop yields are sourced from the FAO.

Table 3 shows that extreme heat shocks cause food prices in destination countries to diverge, similarly to the pattern observed following the onset of the Ukraine war. The estimates in the table come from a panel regression with country and year fixed effects. Column 1 shows that each source country KDD raises domestic food CPI 0.5%. Given the control for year fixed effects, this coefficient shows that extreme heat raises *relative* food prices in destination countries, as compared with the global average - exactly the pattern observed in the Ukraine war event study in Figure 5. Column 2 shows that the result holds when controlling for domestic KDD and GDD as well, with a slightly smaller coefficient likely due to the covariance between foreign and domestic shocks. Column 3 shows that source KDD have negligible effects on domestic crop yields, and Column 4 shows that exposure to source country KDD raises agricultural imports - though likely

with trade diversion across sources.

Overall, we interpret the results from Table 3 as further evidence of market segmentation. If global trade in agricultural goods was perfectly integrated across locations, we would expect productivity shocks in a given country to have uniform effects on world prices. Instead, what we observe both in the context of the Ukraine war and in response to extreme heat shocks is that price increases are disproportionately concentrated in export destinations of the affected country, suggesting frictions in substituting across source country trade partners at least in the short run.

4 Model

Motivated by the empirical evidence presented above, we develop a multi-country general equilibrium model of sourcing decisions in the agricultural sector under risk. We first specify preferences and endowments that characterize the riskless trade equilibrium with exogenous sourcing following Gaigné and Gouel (2022b). We then embed the trade equilibrium in a stochastic environment in which sourcing decisions are made under risk.

4.1 Riskless environment

4.1.1 Import demand

Consider a world consisting of J countries, each of which has a representative consumer that derives utility from consuming an outside good, C_j^o, and an agricultural composite, C_j:

$$U_j = C_j^o + \zeta_j \ln C_j. \tag{4}$$

The total demand for crops depends only on a country-specific demand shifter, $\zeta_j \geq 0$.

The agricultural composite, C_j, depends on the consumption of each crop, C_j^k, which itself depends on the consumption of a continuum of varieties, $C_j^k(\omega)$:

$$C_j = \left[\sum_{k \in \mathcal{K}} \left(\zeta_j^k \right)^{\frac{1}{\kappa}} \left(C_j^k \right)^{\frac{\kappa-1}{\kappa}} \right]^{\frac{\kappa}{\kappa-1}} \tag{5}$$

where $\mathcal{K}$ denotes the set of crops, $\kappa > 0$ denotes the elasticity of substitution between

them, and $\zeta_j^k \geq 0$ is a crop-importer-specific demand shifter, and

$$C_j^k = \left[\int_{\omega \in \Omega_j^k} \left(\zeta_j^k(\omega) \right)^{\frac{1}{\sigma}} \left(C_j^k(\omega) \right)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where Ω_j^k is the set of varieties of crop k available to consumers in country i, $\sigma > 1$ denotes the elasticity of substitution between those varieties, and $\zeta_j^k(\omega) \geq 0$ is a variety-importer-specific demand shifter.

These preferences give rise to the following demand in country i for variety ω of crop k:

$$C_j^k(\omega) = \zeta_j^k(\omega) \frac{E_j^k}{P_j^k} \left(\frac{P_j^k}{p_j^k(\omega)} \right)^{\sigma}, \tag{7}$$

where $p_j^k(\omega)$ is the price of variety ω, P_j^k is the standard ideal price index associated with the CES aggregator in (6), and E_j^K is aggregate spending on crop k in country i.

4.1.2 Technology

Crop varieties are produced by a competitive fringe of farmers who sell their output at marginal cost. The unit cost function for variety ω of crop k in country i is assumed to take the form $c_i^k / z_i^k(\omega)$, where $z_i^k(\omega)$ follows a Fréchet distribution with a shape parameter $\theta > \sigma - 1$ and a scale parameter scale parameter T_i^k.[12] Shipping crops from country i to country j entails iceberg trade costs $\delta_{ij}^k \geq 1$.

The outside good is produced with constant returns to scale in labor only with productivity T_i^o. It is homogeneous, freely traded, and therefore used as the numeraire.

4.1.3 Consumer prices and gravity

Let $\mathcal{J}_j^k \subseteq J$ denote the set of countries from which the consumer in country j can import varieties of crop k.[13] Conditional on the sourcing strategy set, the price at which the consumer in country i purchases variety ω of crop k is given by

$$p_j^k(\omega) = \min_{i \in \mathcal{J}_j^k} \left\{ \delta_{ij}^k \frac{c_i^k}{z_i^k(\omega)} \right\} \tag{8}$$

[12] This formulation encompasses the standard Ricardian case in which labor is the only factor of production, so $c_i^k = w_i$, as well as more general formulations in which land and intermediates are also used in production, potentially with intensities that vary by crop.

[13] We take this set as exogenous for now and specify how it is determined once we introduce risk.

Using the properties of the Fréchet distribution, one can show that the consumer will source a positive measure of varieties from each country in its sourcing strategy set for each crop, $\mathcal{J}_j^k$. Furthermore, the share of varieties sourced from any country i (including the home country j) is given by

$$\lambda_{ij}^k = \frac{T_i \left(\delta_{ij}^k c_i^k\right)^{-\theta}}{\Theta_j^k} \quad \text{if } i \in \mathcal{J}_j^k, \tag{9}$$

and $\lambda_i j^k = 0$ otherwise, where

$$\Theta_j^k \equiv \sum_{n \in \mathcal{J}_j^k} T_n^k \left(\delta_{nj}^k c_n^k\right)^{-\theta} \tag{10}$$

summarizes the sourcing capability of country j for crop k.

4.2 Trade equilibrium

In a trade equilibrium, all consumers maximize their utility, all firms maximize their profits, and all markets clear, taking endowments and policies as given.

4.3 Sourcing decisions under risk

We now embed the trade equilibrium in a stochastic environment. Let $s \in \mathcal{S}$ denote the state of the world, and let $\pi(s)$ denote the probability of state s. We assume that only bilateral trade costs (inclusive of ad-valorem policies) and unit costs vary across states.[14] It will therefore be sufficient to index trade equilibria by the prices that are realized in each state, $p_j^k(\omega, s)$. Let $U_j(s)$ denote the ex-post utility of the representative consumer in country j in state s.

Before the realization of the state, the representative consumer in country j chooses a sourcing strategy $\mathcal{J}_j^k$ for each crop k.[15] To add country i to the set $\mathcal{J}_j^k$, the consumer must pay a fixed cost f_{ij}^k in units of the outside good.[16]

The consumer's problem is to choose a sourcing strategy $\mathcal{J}_j^k$ that maximizes her ex-

[14] In particular, idiosyncratic shocks to productivity are assumed to obey the same distribution regardless of which aggregate state is realized.

[15] The sourcing problem follows Antràs, Fort and Tintelnot (2017). See also Farrokhi (2020).

[16] This fixed cost can be interpreted as a sunk cost of establishing relationships with suppliers in country i or of evaluating suppliers against sanitary and phytosanitary (SPS) standards.

ante expected utility:[17]

$$\max_{I_{ij}^k \in \{0,1\}} [U_j(s)] = \sum_{s \in \mathcal{S}} \pi(s) \left[\left(C_i^o(s) - \sum_{i,k} I_{ij}^k f_{ij}^k \right) + \zeta_i \ln C_i(s) \right]. \tag{11}$$

5 Calibration

In future drafts of the paper, we will present a strategy to calibrate the parameters for the model presented in the previous section. Many of the parameters concerning consumer demand, agricultural production, and trade costs can be calibrated using strategies that follow directly from Costinot, Donaldson and Smith (2016) and Carleton, Crews and Nath (2023). The key new parameters to estimate in this paper are the fixed costs to import sourcing, which follow closely from the measure of import source diversification we use throughout the empirical section of the paper.

6 Counterfactuals

We plan to consider the following counterfactual policy scenarios in the paper. First, we plan to vary trade costs, starting with the levels estimated to match existing trade flows, and comparing against policy scenarios without trade (autarky) and with substantial trade liberalization. Second, we plan to consider scenarios that specifically subsidize import source diversification (or perhaps equivalently, remove regulatory barriers to adding import sources). Third, we plan to consider scenarios that follow from more traditional "food sovereignty" policies that raise import tariffs and subsidize domestic production. For each counterfactual, our primary focus will be the volatility of food prices, consumption, and welfare.

7 Conclusion

This paper evaluates the conventional wisdom among many policymakers that food security is best achieved by promoting reliance on domestic production for food. In contrast to this hypothesis, we show that food prices show less sensitivity to domestic weather shocks in countries with greater trade integration. We emphasize that a measure of import

[17] *Disclaimer*: We are still considering what preferences over states of the world make the most sense in this context.

source diversification, rather than the agricultural trade share, best predicts the reduced transmission of extreme heat into food prices.

Consistent with policymaker concerns about reliance on foreign production, we also show that importing countries face vulnerability to environmental and geopolitical shocks in countries from which they source. The disruption to food exports following the onset of the Russia-Ukraine war, as well as extreme heat shocks more generally, both cause prices to diverge across locations and rise disproportionately in the export destinations of the affected countries. This suggests that global agricultural markets are segmented, and that importers may face delays and barriers to switching across import sources and allowing prices to equalize across locations in the short run.

While we cannot evaluate policy scenarios in this draft of the paper, which does not yet contain model counterfactual results, we note that the empirical results suggest that import source diversification protects countries against the ex ante risk of both foreign and domestic environmental and geopolitical shocks. Given that averaging crop yields across countries and across continents reduces volatility from idiosyncratic variability, the ability to source food from many locations is likely to reduce exposure to productivity shocks, policy shocks, and conflicts affecting any particular part of the world. It is possible this mechanism would break down in the face of shocks with a systematic enough global component, however, such as widespread climate disaster or simultaneous implementation of policy barriers such as the export bans imposed during the COVID pandemic. In future drafts of the paper, we hope to provide more concrete conclusions about the conditions under which trade openness does and does not promote food security.

References

Adamopoulos, Tasso and Fernando Leibovici, *Trade Risk and Food Security*, Federal Reserve Bank of St. Louis, Research Division, 2024.

Allen, Treb and David Atkin, "Volatility and the Gains from Trade," *Econometrica*, 2022, *90* (5), 2053–2092.

Antràs, Pol, Teresa C. Fort, and Felix Tintelnot, "The margins of global sourcing: Theory and evidence from US firms," *American Economic Review*, September 2017, *107* (9), 2514–2564.

Baptista, Diogo, John A Spray, and Filiz Unsal, *Coping with climate shocks: Food security in a spatial framework*, International Monetary Fund, 2025.

Brooks, Wyatt and Kevin Donovan, "Eliminating Uncertainty in Market Access: The Impact of New Bridges in Rural Nicaragua," *Econometrica*, 2020, *88* (5), 1965–1997.

Burgess, Robin and Dave Donaldson, "Can openness mitigate the effects of weather shocks? Evidence from India's famine era," *American Economic Review*, 2010, *100* (2), 449–453.

Burke, Marshall and Kyle Emerick, "Adaptation to climate change: Evidence from US agriculture," *American Economic Journal: Economic Policy*, 2016, *8* (3), 106–140.

Carleton, Tamma, Levi Crews, and Ishan Nath, "Agriculture, trade, and the spatial efficiency of global water use," Technical Report, Working paper 2023.

Caselli, Francesco, Miklos Koren, Milan Lisicky, and Silvana Tenreyro, "Diversification through trade," *The Quarterly Journal of Economics*, 2020, *135* (1), 449–502.

Castro-Vincenzi, Juanma, Gaurav Khanna, Nicolas Morales, and Nitya Pandalai-Nayar, "Weathering the storm: Supply chains and climate risk," Technical Report, National Bureau of Economic Research 2024.

Conte, Bruno, Klaus Desmet, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg, "Local sectoral specialization in a warming world," *Journal of Economic Geography*, 2021, *21* (4), 493–530.

Costinot, Arnaud, Dave Donaldson, and Cory Smith, "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*, 2016, *124* (1), 205–248.

Dingel, Jonathan I, Kyle C Meng, and Solomon M Hsiang, "Spatial correlation, trade, and inequality: Evidence from the global climate," Technical Report, National Bureau of Economic Research 2019.

Farrokhi, Farid, "Global sourcing in oil markets," *Journal of International Economics*, July 2020, *125*, 103323.

_ and Heitor S Pellegrina, "Trade, technology, and agricultural productivity," *Journal of Political Economy*, 2023, *131* (9), 2509–2555.

Gaigné, Carl and Christophe Gouel, "Trade in agricultural and food products," *Handbook of agricultural economics*, 2022, *6*, 4845–4931.

Gaigné, Carl and Christophe Gouel, "Trade in agricultural and food products," in "Handbook of Agricultural Economics," Elsevier, 2022, pp. 4845–4931.

Gaulier, Guillaume and Soledad Zignago, "BACI: International Trade Database at the Product-Level. The 1994-2007 Version," Working Papers 2010-23, CEPII 2010.

Gouel, Christophe, *Food Price Volatility and Domestic Stabilization Policies in Developing Countries*, University of Chicago Press, October

_ , "Trade policy coordination and food price volatility," *American Journal of Agricultural Economics*, 2016, *98* (4), 1018–1037.

_ and David Laborde, "The crucial role of domestic and international market-mediated adaptation to climate change," *Journal of Environmental Economics and Management*, 2021, *106*, 102408.

_ and Sébastien Jean, "Optimal food price stabilization in a small open developing country," *The World Bank Economic Review*, 2015, *29* (1), 72–101.

Grossman, Gene M, Elhanan Helpman, and Hugo Lhuillier, "Supply chain resilience: Should policy promote international diversification or reshoring?," *Journal of Political Economy*, 2023, *131* (12), 3462–3496.

Headey, Derek, "Rethinking the global food crisis: The role of trade shocks," *Food Policy*, 2011, *36* (2), 136–146.

Helpman, Elhanan and Assaf Razin, "The protective effect of a tariff under uncertainty," *Journal of Political Economy*, 1978, *86* (6), 1131–1141.

Hsiao, Allan, Jacob Moscona, and Karthik Sastry, "Food Policy in a Warming World," 2024, *32539*.

Hultgren, Andrew, Tamma Carleton, Michael Delgado, Diana R Gergel, Michael Greenstone, Trevor Houser, Solomon Hsiang, Amir Jina, Robert E Kopp, Steven B Malevich et al., "Estimating global impacts to agriculture from climate change accounting for adaptation," *Available at SSRN 4222020*, 2022.

Jacks, David S, Kevin H O'Rourke, and Jeffrey G Williamson, "Commodity price volatility and world market integration since 1700," *Review of economics and statistics*, 2011, *93* (3), 800–813.

Leibovici, Fernando and Ana Maria Santacreu, "Shortages of critical goods in a global economy: Optimal trade and industrial policy," *Federal Reserve Bank of St. Louis Working Paper*, 2023.

Liddell, Tyler, Anna S Boser, Sara Orofino, Tracey Mangin, and Tamma Carleton, "stagg:: A data pre-processing R package for climate impacts analysis," *Environmental Modelling & Software*, 2025, *183*, 106202.

Moscona, Jacob and Karthik A Sastry, "Does directed innovation mitigate climate damage? Evidence from US agriculture," *The Quarterly Journal of Economics*, 2023, *138* (2), 637–701.

Nath, Ishan, "Climate change, the food problem, and the challenge of adaptation through sectoral reallocation," 2025.

Porteous, Obie, "High trade costs and their consequences: An estimated dynamic model of African agricultural storage and trade," *American Economic Journal: Applied Economics*, 2019, *11* (4), 327–366.

Ramankutty, Navin, Amato T Evan, Chad Monfreda, and Jonathan A Foley, "Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000," *Global biogeochemical cycles*, 2008, *22* (1).

Rivera-Padilla, Alberto, "Crop choice, trade costs, and agricultural productivity," *Journal of development economics*, 2020, *146*, 102517.

Roberts, Michael J and Wolfram Schlenker, "Identifying supply and demand elasticities of agricultural commodities: Implications for the US ethanol mandate," *American Economic Review*, 2013, *103* (6), 2265–2295.

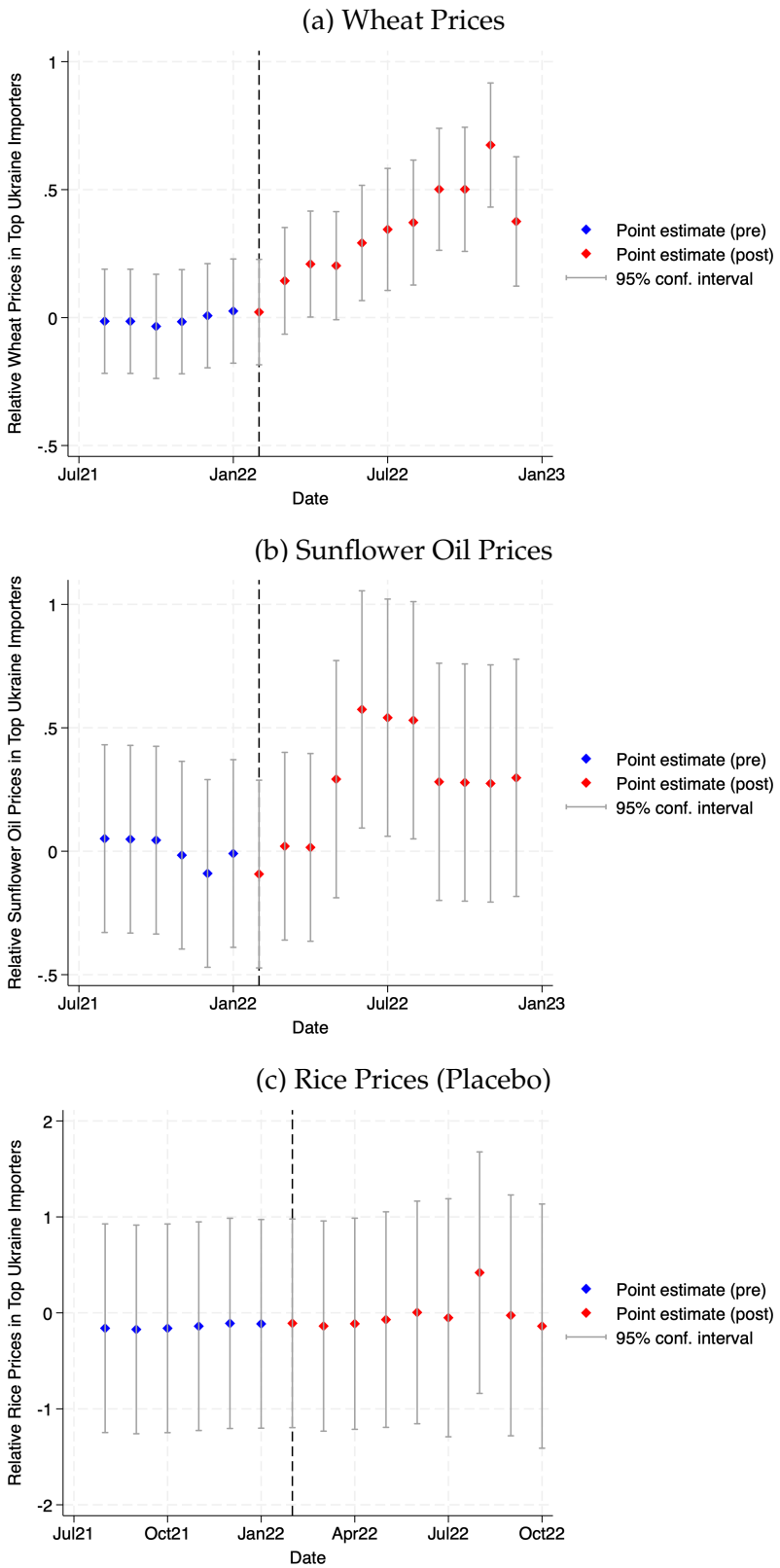
Schlenker, Wolfram and Michael J Roberts, "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of sciences*, 2009, *106* (37), 15594–15598.

Stiglitz, Joseph E and David MG Newbery, "Pareto Inferior Trade," 1984.

Tombe, Trevor, "The missing food problem: Trade, agriculture, and international productivity differences," *American Economic Journal: Macroeconomics*, 2015, *7* (3), 226–258.

A Appendix

Figure A-1: Differential Impact of Ukraine War on Food Prices in Direct Importers



Notes: Panel (a) plots coefficients for an event study regressing monthly wheat prices on a month-by-top-importer indicator, where top importer is defined as a country in the top quartile of Ukrainian wheat imports. Uninteracted month coefficients are omitted from the graph but included in the regression. Months displayed are those preceding and following Russia's invasion of Ukraine in February 2022. Panel (b) shows the same specification with sunflower oil prices as the dependent variable and top importer status defined by sunflower oil imports. Panel (c) serves as our placebo using rice prices as the dependent variable and top wheat importer status. All regressions include month and country fixed effects. Outcome variable data comes from WFP consumer price data. Exposure to Ukrainian imports is constructed using crop-level BACI trade flows and FAO consumption data.