Global Food Security and the El Niño-Southern Oscillation

Aidan J. Wang*

University of California, Berkeley

May 15, 2020

Abstract

Food security has been suggested to be linked to the global climate, but past literature has only focused on the effects of local weather conditions, inadequate analogs for global climate variables. I study the effects of the El Niño-Southern Oscillation (ENSO), a dominant, warm-cool mode in the global climate that affects local climates in so-called ENSO-teleconnected areas, on food security within countries and regions. I find insignificant ENSO effects on food supply within countries, despite documented, negative ENSO effects on agricultural production and macroeconomies, implying that national food markets smooth these effects. However, ENSO significantly increases food prices within countries, presumably due to the market actions required to stabilize food supply. These rising food prices may be paralleled by increases in undernourishment in ENSO-teleconnected regions and, to a lesser extent, in other regions, suggesting that ENSO reduces nourishment of vulnerable households through price changes despite stability in national food supply.

*This senior thesis was written for the Honors Program in the Department of Economics at the University of California, Berkeley. I am immensely grateful to my advisor, Edward Miguel, for his guidance, encouragement, and helpful comments and discussions. I also thank Oliver Kim, Kyra Frye, Serra Pelin, and Felipe González for very helpful comments.

1 Introduction

Food security has been suggested to be linked to the global climate since modern, globalized food systems rest on agricultural production (that depends on sunlight and rainfall) around the globe. The literature has focused on documenting the effects of local weather conditions such as temperature and precipitation on food security (Misselhorn 2005; Demeke, Keil, and Zeller 2011; Nyariki, Wiggins, and Imungi 2002). While local conditions are important climatic factors, they are inadequate analogs for understanding how global climate conditions affect food security. Global changes in the climate are inherently different from local weather shocks: they may affect socioeconomic outcomes through channels beyond temperature and precipitation, they may be correlated over large regions, and they may be (at least partially) predictable (Hsiang, Meng, and Cane 2011). Studies of local weather conditions fail to account for these effects.

In this paper, I study the effect on food security of a dominant mode in the global climate, the El Niño-Southern Oscillation (ENSO). El Niño events are oceanic warming events in the tropical Pacific Ocean (Timmermann et al. 2018; Wang et al. 2017) that are propagated by atmospheric waves around the globe, affecting local climate conditions in so-called ENSO-teleconnected areas (Chiang and Sobel 2002; Halpert and Ropelewski 1992; Trenberth and Caron 2000; C. F. Ropelewski and M. S. Halpert 1987). La Niña events are oceanic cooling events that impact the global climate in generally opposite ways to El Niño. ENSO is the repeated shifting between EL Niño and La Niña phases with a period of three to seven years and is the strongest and most predictable interannual fluctuation in the global climate (Chen and Cane 2008).

Building off the research designs in Hsiang, Meng, and Cane (2011) and Hsiang and Meng (2015), I match a continuous index of the global state of ENSO with panel data on three food security outcomes—food supply per capita per day and Food Consumer Price Index (Food CPI) at the country level, which together summarize the response of national food markets, and prevalence of undernourishment at the regional level. I separate countries and regions into a group that is ENSO-teleconnected and a group that is weakly affected by ENSO and estimate average within-country or within-region ENSO effects on the three outcomes separately for these two groups. I use a set of regression specifications that allow for potentially nonlinear ENSO effects.

Looking first at national food markets, I find small and insignificant ENSO effects on food supply per capita per day in both ENSO-teleconnected and weakly affected countries. Compared with documented, mostly negative El Niño effects on agricultural production (Iizumi et al. 2014; Hsiang and Meng 2015) and macroeconomies (Cashin, Mohaddes, and Raissi 2017; Smith and Ubilava 2017) in ENSO-teleconnected countries, the stability of food supply implies that food markets are able to quite successfully smooth these ENSO effects at the country-year level. However, I also find that for ENSO-teleconnected countries, El Niño years and weak La Niña years increase Food CPI by 0 to 4% of 2010 prices, while strong La Niña years decrease Food CPI by 5% of 2010 prices, on average. In weakly affected countries, El Niño years and weak La Niña years increase Food CPI by 1 to 6% of 2010 prices, and strong La Niña years decrease Food CPI by 1% of 2010 prices, on average. These significant effects on food prices suggest that the market actions necessary to keep food supply stable are associated with changing costs of procuring food. Furthermore, the parallel effects observed in the two country groups imply that these food price effects may spillover from ENSO-teleconnected to weakly affected countries.

Turning to undernourishment, I find that in ENSO-teleconnected regions, El Niño years and weak La Niña years may increase prevalence of undernourishment by 0.2 to 0.8pp, while strong La Niña years reduce it by 0.9pp, on average. In weakly affected regions, El Niño years increase prevalence of undernourishment by 0.1 to 0.3pp, and La Niña years decrease it by 0.1 to 0.2pp, on average. This suggests that the observed stability in food supply belies significant food losses for certain vulnerable households and that rising food prices play a role in this ENSO-driven undernourishment, and more so for ENSO-teleconnected regions than for weakly affected ones. Taken together, the results show that, on average, ENSO-driven instabilities in food security look not like massive food shortages but rather like food price fluctuations that only affect the nourishment of vulnerable households. This effect is more pronounced in ENSO-teleconnected areas.

The Food and Agricultural Organization (FAO) defines food security as "a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, IFAD, UNICEF, WFP and WHO 2019). Four sequential dimensions of food security follow from this definition: food *availability*, *access*, *utilization*, and the *stability* of the previous three (Pinstrup-Andersen 2009). This study therefore identifies ENSO to be a significant factor in the stability of food access but not food availability, echoing the recent focus in the food security literature on food access over food availability.

This paper contributes to the literature on climatic causes of food insecurity. Qualitative and quantitative literature have linked local weather conditions with household food security (Misselhorn 2005; Demeke, Keil, and Zeller 2011; Nyariki, Wiggins, and Imungi 2002). This study complements existing studies on local weather shocks by identifying ENSO, a global climatic variable, as another climatic determinant of food insecurity, a linkage which to my knowledge has not been previously quantified. It also documents climate as a factor for food security at larger macro levels.

This paper also contributes to the large literature on the effects of ENSO on various socioeconomic outcomes around the globe. ENSO has been found to affect agricultural yields and production (Iizumi et al. 2014; Hsiang and Meng 2015), macroeconomic variables (Cashin, Mohaddes, and Raissi 2017; Smith and Ubilava 2017; Brunner 2002), human diseases (Kovats et al. 2003; Hales, Edwards, and Kovats 2003; Patz et al. 2005), and civil conflict (Hsiang, Meng, and Cane 2011) throughout the globe. This study extends the literature on global ENSO effects to food security outcomes.

The paper proceeds as follows. Section 2 describes ENSO and how it may affect global food security. Section 3 summarizes the data on ENSO and the three food security outcomes and describes the analysis methodology. Section 4 summarizes the responses of national food markets using the results for the food supply and food prices outcomes and provides discussion. Section 5 turns to the results for the undernourishment outcome and discusses. Section 6 concludes.

2 The El Niño-Southern Oscillation

El Niño climate phenomena are oceanic warming events that occur in the tropical Pacific Ocean and consist of an increase in sea surface temperature (SST) and a weakening of equatorial trade winds (Timmermann et al. 2018; Wang et al. 2017). This warming generates atmospheric waves which propagate the warming around the globe and affect local climate conditions in so-called ENSO-teleconnected areas: generally, the tropics (Chiang and Sobel 2002). La Niña phenomena are oceanic cooling events in the tropical Pacific Ocean that impact the global climate in generally opposite ways to El Niño. The repeated shifting between El Niño and La Niña phases is known as the El Niño-Southern Oscillation (ENSO) and has a period of three to seven years. It is the strongest and most predictable source of interannual fluctuation in the global climate.

ENSO affects local temperature, precipitation, and tropical storms throughout the world (Halpert and Ropelewski 1992; Trenberth and Caron 2000; C. F. Ropelewski and M. S. Halpert 1987; Chester F. Ropelewski and Michael S. Halpert 1996; Camargo and Sobel 2005; Donnelly and Woodruff 2007). Generally, El Niño years increase temperature and decrease rainfall in ENSO-teleconnected areas and have opposite but weaker effects in weakly affected areas (Hsiang and Meng 2015). In turn, increased local temperature and decreased local precipitation have been found to have negative effects on household food security (Misselhorn 2005; Demeke, Keil, and Zeller 2011; Nyariki, Wiggins, and Imungi 2002). Thus, it is plausible that El Niño is linked with decreased household food security in ENSO-teleconnected areas.

This proposed linkage may have several channels. First, ENSO may affect the supply side of food markets. El Niño years have been found to have mostly negative impacts on agricultural yields and production in ENSO-teleconnected areas and weaker, mostly positive impacts in weakly affected areas (Hsiang and Meng 2015; Iizumi et al. 2014). Depressed agricultural yields and production may translate into reduced food supplies or increased food prices for households.

Second, ENSO may also impact the demand side of food markets. El Niño events have been found to have mixed but mostly negative effects on GDP growth (and thus household incomes and unemployment) in ENSO-teleconnected countries, with weaker, mixed effects in weakly affected countries as well as inflationary effects on world commodity prices (Cashin, Mohaddes, and Raissi 2017; Smith and Ubilava 2017; Brunner 2002). In turn, decreased household incomes and increased unemployment and price levels have been found to decrease food security by intensifying household budget constraints and trade-offs to purchasing food (Loopstra et al. 2016; Bacon et al. 2017; Verpoorten et al. 2013).

El Niño has even been found to exacerbate human diseases (Kovats et al. 2003; Hales, Edwards, and Kovats 2003; Patz et al. 2005) and civil conflict in ENSO-teleconnected countries (Hsiang, Meng, and Cane 2011). Any of these global ENSO effects may be channels through which El Niño reduces food security in ENSO-teleconnected areas, though the main channels are expected to be through negative supply-side effects on agricultural production and negative demand-side effects on macroeconomies due to increased local temperature and decreased local precipitation.

3 Data and Methodology

3.1 Measuring ENSO

The global state of ENSO can be indexed by various climatic variables that reflect physical mechanisms of the phenomenon (Timmermann et al. 2018; Wang et al. 2017). In this study,

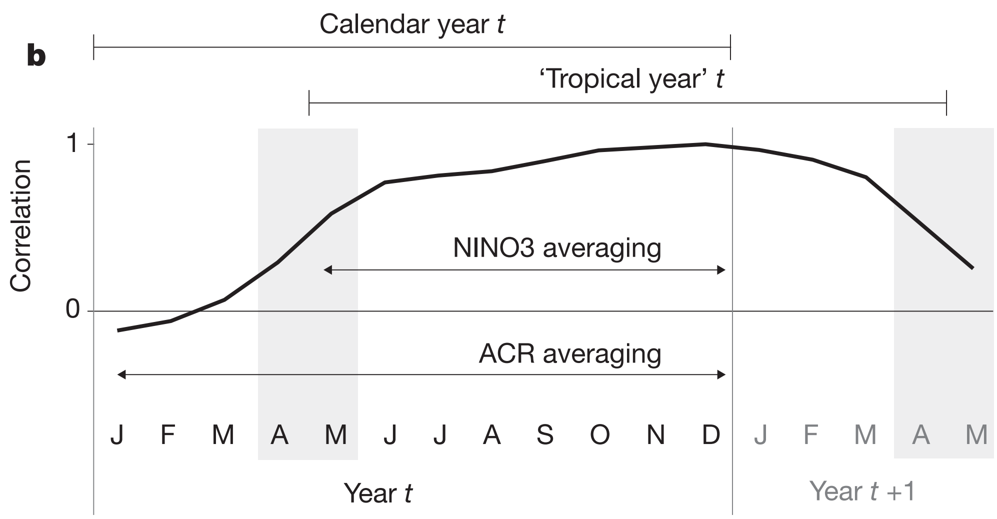


Figure 1: Correlations of Monthly NINO3 with That of December. *Notes:* Calendar year t and its overlapping "tropical year" t from May of year t through April of year $t+1$ are shown. When possible, food security outcomes and NINO3.4 are averaged over tropical year. For food security outcomes with data only at calendar-year intervals (denoted ACR), a contemporaneous annual NINO3.4 index (denoted NINO3) is averaged over May through December. See Hsiang, Meng, and Cane (2011) for details on the latter averaging methodology. Reproduced from Hsiang, Meng, and Cane (2011).

I employ the commonly used NINO3.4 index, defined as the average SST anomaly in the region 5°N–5°S, 170°W–120°W (see Figure 3), using centered 30-year base periods updated every five years. The monthly series is obtained from the Climate Prediction Center (CPC) of the National Oceanic and Atmospheric Administration (Climate Prediction Center Internet Team 2009). The CPC defines months in which the three-month running average is above +0.5°C or below -0.5°C for at least five consecutive months as El Niño or La Niña months, respectively, with larger deviations being stronger events.

Because El Niño and La Niña events typically start in boreal spring and last until the following spring, the "tropical year" t is considered to go from May of year t through April of year $t+1$. Figure 1 shows the correlations of NINO3 (another index similar to NINO3.4) in different months with that of December, when an El Niño or La Niña event typically matures. NINO3 in December of year t is strongly correlated with that of the months from May of year t through April of year $t+1$. Since ENSO occurs at interannual frequencies, I average NINO3.4 over tropical years and do the same for the food security outcome with monthly data. For the food security outcomes with data only at calendar-year frequencies,

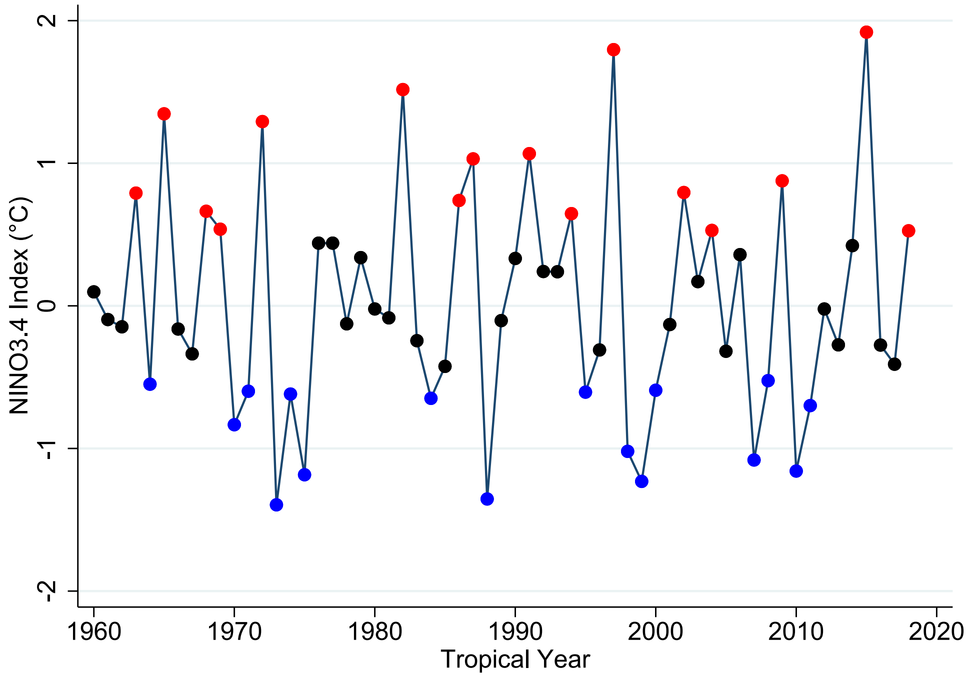


Figure 2: Annual NINO3.4 Series. *Notes:* NINO3.4 averaged over tropical year (May to April of the next calendar year). Years denoted El Niño in red (La Niña in blue) are those in which the majority of months in the tropical year are defined as El Niño (La Niña) months by the Climate Prediction Center (CPC) (Climate Prediction Center Internet Team 2009). Data are from the CPC.

I follow Hsiang, Meng, and Cane (2011) in averaging NINO3.4 over May through December to match outcomes in a given calendar year to the contemporaneous ENSO signal of the overlapping tropical year.

The tropical-yearly NINO3.4 series is plotted in Figure 2. The index ranges from roughly -1.5°C to +2°C. I denote El Niño or La Niña tropical years to be those in which the majority of months in the tropical year are defined as El Niño or La Niña months respectively by the CPC.

ENSO is expected to have differing effects on food security for countries in different regions of the globe because the physical teleconnections that propagate it primarily reach only parts of the globe: generally, the tropics. In order to properly identify these differing effects, I follow the methodology in Hsiang, Meng, and Cane (2011) to split the sample of countries into an ENSO-teleconnected group and a group that is weakly affected by ENSO. Hsiang,

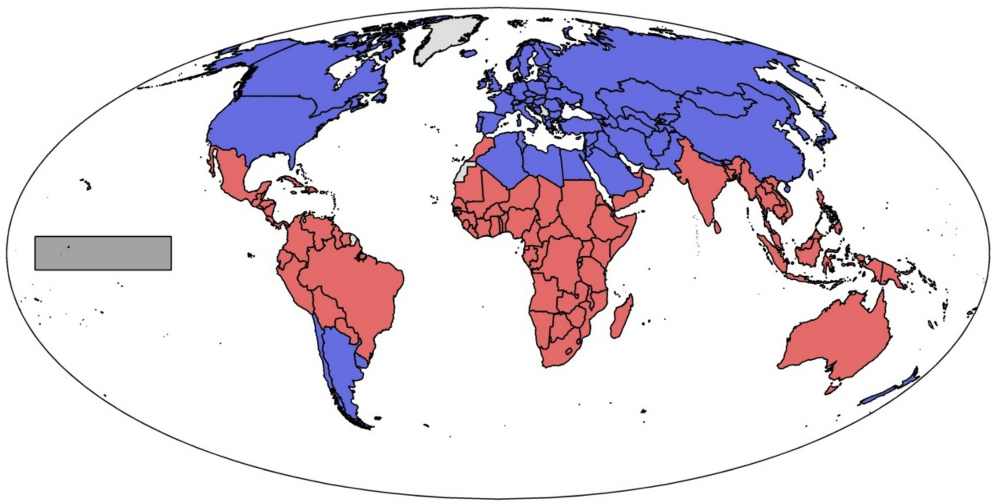


Figure 3: Country Assignment into ENSO-Teleconnected and Weakly Affected Groups. *Notes:* ENSO-teleconnected countries are in red and weakly affected countries are in blue. Light gray countries have no population data so are unassigned. The dark gray rectangle shows the NINO3.4 area over which sea surface temperature anomalies are averaged. See Hsiang, Meng, and Cane (2011) for details on the methodology of country assignment. Reproduced from Hsiang and Meng (2015) Online Appendix.

Meng, and Cane (2011) use local surface temperature to identify ENSO-teleconnected locations for theoretical reasons and because it is less spatially variable than other climatic variables. Global pixels are considered ENSO-teleconnected if surface temperature is positively correlated with NINO3 of two months prior for at least three months. Countries are then assigned ENSO-teleconnected if the majority of their population resides in teleconnected pixels and are deemed weakly affected if not. This binary classification rather than a continuous measure of each country's teleconnection to ENSO is used since Hsiang, Meng, and Cane (2011) find that the distributions of population living in ENSO-teleconnected pixels are near zero or one for the vast majority of countries in their sample. The country assignment is shown in Figure 3 and listed in Table 9 in Appendix C. For analyses of the food security outcome that only has data at the more-aggregated regional level, I assign regions to be either ENSO-teleconnected or weakly affected based on the population-weighted mode of the countries that make up the region. In the analysis that follows, I estimate the effects of ENSO separately for countries or regions in the ENSO-teleconnected group and in the weakly affected group in order to account for potentially differing effects in these two groups.

Note that ENSO may still be expected to have an effect on countries or regions in the weakly affected group due to weaker climatic effects, spillover effects, or general equilibrium effects.

3.2 Measuring Global Food Security

To analyze global food security, I use panel data on three food security outcomes—food supply and food prices at the country level and undernourishment at the regional level. The food supply and food prices outcomes together summarize national food markets, while the undernourishment outcome sheds light on household access to these markets. The three outcomes provide interrelated and complementary perspectives on the stability of the food-availability and food-access dimensions of food security. To measure these outcomes, I utilize various datasets in the FAOSTAT database of the FAO (FAO 2019).

3.2.1 Measuring Food Supply

To measure food supply, I use the variable food supply per capita per day measured annually at the country level from 1961 to 2013 from the historical Food Balance Sheets dataset in the FAOSTAT database (FAO 2019). The annual food supply of a country equals the sum of the quantity of food produced in that country, the net quantity imported, and the net change in stocks, minus the quantity not for human consumption. The measure is expressed as the average number of calories available to every person every day in a given country-year.

In this analysis, I only consider sovereign and constituent countries because they constitute complete economies and food systems; dependencies are omitted. Countries with fewer than three years of data are also dropped because the series can be perfectly fit by the country-specific linear trend in the regression specification. Table 1 presents summary statistics for the food supply per capita per day outcome separately for the ENSO-teleconnected and weakly affected country groups. The ENSO-teleconnected group contains 92 countries and 53 years for a total of 4,815 observations, while the weakly affected group contains 77 countries and 53 years for a total of 3,260 observations. For the food supply per capita per

Table 1: Summary Statistics for the Food Supply Per Capita Per Day Outcome by Country Group

	ENSO-teleconnected			Weakly affected		
	Mean	SD	SD within	Mean	SD	SD within
Food supply/capita/day (kcal)	2,311	377	237	2,930	461	253
Food supply/capita/day 1961-1969 (kcal)	2,094	300	84	2,687	491	93
Food supply/capita/day 1970-1979 (kcal)	2,192	341	103	2,821	471	109
Food supply/capita/day 1980-1989 (kcal)	2,311	381	103	2,960	417	96
Food supply/capita/day 1990-1999 (kcal)	2,340	365	79	2,931	448	124
Food supply/capita/day 2000-2009 (kcal)	2,479	345	80	3,055	425	86
Food supply/capita/day 2010-2013 (kcal)	2,592	329	35	3,123	377	30
Countries	92			77		
Years	53			53		
Observations	4,815			3,260		

Notes: Each observation is a country-year and the sample period is 1961-2013. Summary statistics are displayed separately for the ENSO-teleconnected and weakly affected country groups. The summary statistic “SD within” is the standard deviation of food supply per capita per day over the given period after subtracting country means for that period from each observation. Data are from the historical Food Balance Sheets dataset in the FAOSTAT database (FAO 2019).

day outcome, over several time periods, the table gives the average, standard deviation, and standard deviation “within” countries after subtracting from each observation the country mean for that period. For a point of reference, the U.S. Department of Health and Human Services and U.S. Department of Agriculture (2015) estimate that adult women require 1,600 to 2,400 kcal per day and adult men 2,000 to 3,000. A couple patterns emerge. Average food supply per capita per day over the entire study period was lower in the ENSO-teleconnected group (2,311 kcal) than the weakly affected group (2,930 kcal). Average food supply per capita per day increased in almost every decade from the 1960s to the 2010s for both groups.

3.2.2 Measuring Food Prices

To measure food prices, I use the variable Food Consumer Price Index (Food CPI) measured at the country level monthly from January 2000 to July 2019 from the Consumer Price Indices dataset in the FAOSTAT database (FAO 2019). The Food CPI measures the nominal price level of an average basket of food and beverages purchased by households as a percentage of the price level in the reference year, 2010. I divide each Food CPI country series by the general Consumer Price Index country series with reference year 2010 to obtain a measure

Table 2: Summary Statistics for the Food Consumer Price Index Outcome by Country Group

	ENSO-teleconnected			Weakly affected		
	Mean	SD	SD within	Mean	SD	SD within
Food CPI (2010 = 100)	100.75	10.94	9.73	99.44	6.25	5.28
Food CPI 2000-2009 (2010 = 100)	106.33	12.75	7.72	101.58	7.38	3.70
Food CPI 2010-2018 (2010 = 100)	96.76	7.14	4.14	97.66	4.38	2.46
Countries	75			69		
Tropical years	19			19		
Observations	1,060			1,066		

Notes: Each observation is a country-tropical-year and the sample period is (tropical years) 2000-2018. Summary statistics are displayed separately for the ENSO-teleconnected and weakly affected country groups. The summary statistic "SD within" is the standard deviation of Food Consumer Price Index over the given period after subtracting country means for that period from each observation. Data are from the Consumer Price Indices dataset in the FAOSTAT database (FAO 2019).

of the real price level of an average basket of food and beverages as a percentage of 2010 prices in each country.

As with the food supply outcome, only sovereign and constituent countries are included in the study sample. In order to analyze the Food CPI with respect to interannual ENSO frequencies, the monthly country series are averaged over tropical years (May to April of the following year) for tropical years with all twelve months of data. Countries unable to be assigned to the ENSO-teleconnected or weakly affected group are dropped, as are countries with fewer than three tropical years of data as with the food supply outcome. Table 2 presents the summary statistics for the Food CPI outcome for the ENSO-teleconnected and weakly affected country groups. The ENSO-teleconnected group contains 75 countries and 19 tropical years for a total of 1,060 observations, and the weakly affected group contains 69 countries and 19 tropical years for 1,066 total observations. Since the Food CPI measures prices as a percentage of 2010 prices in each country, cross-country comparisons of food prices can only be made relative to each country. However, a trend emerges that for both country groups, the average Food CPI fell from the 2000s to the 2010s.

Table 3: Summary Statistics for the Prevalence of Undernourishment Outcome by Region Group

	ENSO-teleconnected			Weakly affected		
	Mean	SD	SD within	Mean	SD	SD within
PoU (%)	15.20	10.28	2.68	4.83	4.38	1.45
PoU 2000-2009 (%)	16.80	11.10	1.92	5.29	4.86	0.97
PoU 2010-2018 (%)	13.42	9.03	0.84	4.31	3.72	0.67
Regions	10			9		
Years	19			19		
Observations	190			171		

Notes: Each observation is a region-year and the sample period is 2000-2018. Summary statistics are displayed separately for the ENSO-teleconnected and weakly affected region groups. The summary statistic "SD within" is the standard deviation of prevalence of undernourishment over the given period after subtracting country means for that period from each observation. Data are from the Food Security Indicators dataset in the FAOSTAT database (FAO 2019).

3.2.3 Measuring Undernourishment

To measure undernourishment, I use the variable prevalence of undernourishment (PoU) computed at the country-aggregated regional level annually from 2000 to 2018 from the Food Security Indicators dataset in the FAOSTAT database (FAO 2019). The prevalence of undernourishment estimates the percentage of the population whose dietary energy intake is below the Minimum Dietary Energy Requirement (MDER) necessary for normal and healthy living and is the main indicator used by the FAO to track macro-level trends in food security.

Table 3 displays summary statistics for the prevalence of undernourishment outcome for the ENSO-teleconnected and weakly affected region groups. The ENSO-teleconnected group contains 10 regions and 19 years for 190 total observations, while the weakly affected group has 9 regions and 19 years for a total of 171 observations. Due to the short sample period and few number of regions, analyses using this outcome are unfortunately statistically underpowered, so I treat results using this outcome as suggestive evidence in this paper. Several patterns are notable from the summary statistics. Average prevalence of undernourishment over the sample period was much higher among the ENSO-teleconnected regions (15.20%) than the weakly affected regions (4.83%), with high variation in both groups. In both the 2000s and the 2010s, most of the variation in prevalence of undernourishment is due to cross-region differences rather than within-region variation over years. Finally, average prevalence of undernourishment fell from the 2000s to the 2010s in both groups.

3.3 Identification Strategy

ENSO is determined by physical mechanisms in the equatorial Pacific Ocean and is therefore exogenous to the food security outcomes in this analysis (Timmermann et al. 2018; Wang et al. 2017). Because ENSO repeatedly and rapidly shifts the global climate into warmer and colder states, it serves as a quasi-experiment approximating an ideal experiment comparing separate globes in permanent warm and cold ENSO climates, as pointed out by Hsiang, Meng, and Cane (2011). By controlling for country- or region-level time-invariant and trending differences, I use each country or region as a comparison for that same country or region in different ENSO phases and analyze only the time series variation in ENSO and outcomes, as in Hsiang and Meng (2015). Thus, I identify an average within-country or within-region effect of ENSO on various food security outcomes, separately for ENSO-teleconnected and weakly affected countries or regions.

This strategy for identifying the effect of ENSO on food security outcomes purposefully accounts for all channels by which ENSO affects these outcomes. While most of the effects are presumably through changes in agricultural production and macroeconomies due to local temperature and precipitation, they may also include effects due to tropical storms, disease, conflict, or other undocumented channels (Hsiang and Meng 2015). Another important consideration is that ENSO is a globally-correlated climate variable, so all countries or regions of the world are subjected to the exact same ENSO state at the same time (Hsiang, Meng, and Cane 2011). Therefore, identified within-country or within-region ENSO effects are a combination of direct effects of ENSO on that country or region and indirect effects of ENSO on the rest of the globe that spillover to that country or region. Finally, it is noteworthy that the state of ENSO is not random in a given year and is in fact somewhat predictable. Thus, identified effects of ENSO on outcomes are effects of potentially-predicted ENSO variation.

These effects are a combination of the "true" physical effects of the ENSO shock and the effect of planning by human societies.

These considerations imply that the identification of ENSO effects on food security outcomes in this study may be well-suited to extrapolation to the effects of global warming on these food security outcomes. Like ENSO, the average global temperature is a climatic variable that may affect food security outcomes through a multitude of channels, is correlated around the globe, and is somewhat predictable. While the effects of a permanent increase in global average temperature are not necessarily expected to be the same as a permanently warmer ENSO state, the latter effect may be a more useful theoretical comparison than the effects of local, random weather shocks. In this paper, I focus on interpreting the effects of ENSO itself and leave this extrapolation to further research to carefully compare the physical mechanisms of ENSO and global warming.

3.4 Econometric Strategy

In my baseline regression specification, I follow the analysis in Hsiang and Meng (2015) and estimate the linear model

$$Y_{it} = \beta ENSO_t + \gamma ENSO_{t-1} + \theta_i t + \mu_i + \epsilon_{it} \tag{1}$$

where Y_{it} is a food security outcome (food supply per capita per day, Food CPI, or prevalence of undernourishment) in country or region i and tropical or calendar year t depending on the data for the outcome. $ENSO_t$ is indexed by NINO3.4 averaged over tropical year t or May to December of calendar year t, and β and γ estimate effects of ENSO in years t and $t-1$, respectively, on the outcome. θ_i are country- or region-specific trends and μ_i are country or region fixed effects. ϵ_{it} captures the residual error. I estimate the model separately for the ENSO-teleconnected and weakly affected country or region groups.

I estimate the contemporaneous and one-year-lagged effects of ENSO on food security outcomes since El Niño and La Niña events can last more than one calendar or tropical year, may cause persistent or delayed effects that only materialize after a year, or may have temporal displacement effects, in which case the contemporary and one-year-lagged effects are of opposite sign. Furthermore, Hsiang and Meng (2015) and Cashin, Mohaddes, and Raissi (2017) document contemporaneous and one-year-lagged ENSO effects on agricultural production and macroeconomies, respectively, which are hypothesized to be the main channels through which ENSO affects food security.

Several considerations mitigate concerns related to time series variation. The inclusion of country- or region-specific linear trends addresses non-stationarity in the outcome variables Y_{it}. Meanwhile, the explanatory variable $ENSO_t$ indexed by NINO3.4 is stationary since NINO3.4 is defined as the average SST anomaly using centered and updated base periods. The residual errors ϵ_{it} are allowed to be spatially correlated within 2,000 km and serially correlated over five years for regressions at the country-year level as in Hsiang and Meng (2015) or within 4,000 km for regressions at the region-year level (Conley 1999; Hsiang 2010). I use alternative distances and time lags to check results for robustness in Appendix C. I use the centroid of each country or the population-weighted-averaged centroids of countries composing each region to approximate economic distance between societies for the spatial correlation.

To investigate if ENSO effects on the food security outcomes are nonlinear, I also estimate the cubic model

$$
\begin{aligned}
Y_{it} = {} & \beta_1 ENSO_t + \beta_2 ENSO_t^2 + \beta_3 ENSO_t^3 \\
& + \gamma_1 ENSO_{t-1} + \gamma_2 ENSO_{t-1}^2 + \gamma_3 ENSO_{t-1}^3 + \theta_i t + \mu_i + \epsilon_{it}
\end{aligned}
\tag{2}
$$

where all variables are defined as in Equation 1, and β_n and γ_n estimate the effects of ENSO in years t and $t-1$, respectively, on the outcome. Again, I estimate the model separately for the ENSO-teleconnected and weakly affected country or region groups.

For each country or region group and food security outcome, I compute the F-statistics for the joint statistical significance of the quadratic and cubic coefficients on ENSO in year t (β_2, β_3) and in year $t-1$ (γ_2, γ_3). When there is no significant evidence of a cubic ENSO effect in years t or $t-1$, my preferred specification is the linear model in Equation 1. When there is significant evidence of a cubic ENSO effect in either period, indicating that a nonlinear model could better analyze the effect, my preferred specification is the dummy model

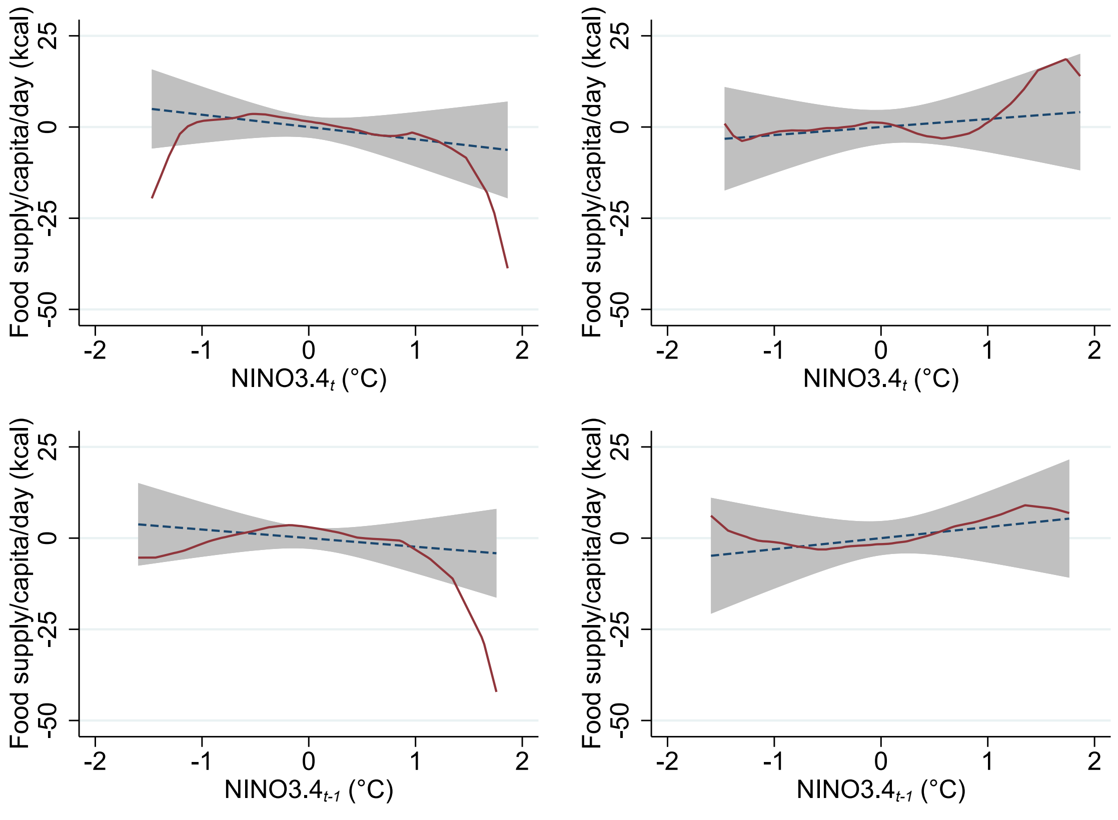
$$Y_{it} = \sum_j (\beta_j 1[ENSO_t \in I_j]) + \sum_j (\gamma_j 1[ENSO_{t-1} \in I_j]) + \theta_i t + \mu_i + \epsilon_{it} \tag{3}$$

where all variables are defined as in Equation 1, I_j are a set of bins dividing the range of $ENSO_t$, and $1[.]$ is the indicator function, a dummy for $ENSO_t$ being in bin I_j. β_j and γ_j estimate the effects of ENSO in years t and $t-1$, respectively, on the outcome.

4 ENSO and National Food Markets

4.1 ENSO and Food Supply

I begin by analyzing the effects of ENSO on food supply at the country-year level. First, I visually inspect the linear fits of the ENSO effects. Figure 4 shows linear and nonparametric fits of food supply per capita per day against NINO3.4 in years t and $t-1$ for the ENSO-teleconnected and weakly affected country groups. In each plot, both food supply per capita per day and NINO3.4 in the period of interest are residualized over NINO3.4 of the other period and country-specific fixed effects and linear trends. Thus, the linear fits match the coefficients of interest estimated in the linear model in Equation 1. 95% confidence intervals are shown for the linear fits using standard errors corrected for spatial correlation within 2,000 km and serial correlation over five years. The nonparametric fits are local-linear kernel regressions using the Epanechnikov kernel with a bandwidth of 0.4. The plots suggest potential nonlinearities in ENSO effects: in ENSO-teleconnected countries, a strong El Niño corresponding to a very high NINO3.4 in years t and $t-1$ appear to be associated with larger



(a) ENSO-Teleconnected

(b) Weakly Affected

Figure 4: Linear Fits of Food Supply Per Capita Per Day Against NINO3.4 By Country Group and Period. *Notes:* Linear and nonparametric fits of food supply per capita per day against NINO3.4 in years t and $t-1$ are shown for the ENSO-teleconnected and weakly affected country groups. For each fit, both food supply per capita per day and NINO3.4 in the period of interest are residualized over NINO3.4 of the other period and country-specific fixed effects and linear trends. Linear fits are in dashed blue with shaded 95% confidence intervals using standard errors corrected for spatial correlation (2,000km) and serial correlation (5 years). Nonparametric fits in solid red are local-linear kernel regressions using the Epanechnikov kernel with bandwidth 0.4.

decreases in food supply per capita per day than the linear model implies, while a strong La Niña corresponding to a very low NINO3.4 in year t may also cause a large decrease rather than a slight increase suggested by the linear model.

In order to test the validity of these suggested nonlinearities, I turn to the estimates of the linear and cubic models in Equations 1 and 2, respectively. Table 4 shows estimates of the two models for both country groups, as well as the F-statistics for the joint significance of the quadratic and cubic NINO3.4 coefficients in years t and $t-1$. For both country groups, the quadratic and cubic NINO3.4 coefficients in year t and $t-1$ are both not jointly

Table 4: Linear and Cubic Regressions of Food Supply Per Capita Per Day on NINO3.4 By Country Group

	ENSO-teleconnected		Weakly affected	
	(1) FS/c/d	(2) FS/c/d	(3) FS/c/d	(4) FS/c/d
NINO3.4_t (°C)	-3.368	-0.696	2.195	4.878
	(3.578)	(7.634)	(4.395)	(9.084)
NINO3.4_t^2 (°C)		-0.934		1.799
		(4.632)		(6.459)
NINO3.4_t^3 (°C)		-2.801		-0.657
		(4.291)		(5.073)
NINO3.4_{t-1} (°C)	-2.362	4.548	3.035	6.634
	(3.458)	(7.387)	(4.669)	(9.000)
NINO3.4_{t-1}^2 (°C)		-3.837		5.498
		(4.925)		(7.558)
NINO3.4_{t-1}^3 (°C)		-4.387		-2.899
		(4.112)		(5.671)
Country fixed effects	Yes	Yes	Yes	Yes
Country-specific linear trends	Yes	Yes	Yes	Yes
Observations	4815	4815	3260	3260
Adjusted R^2	0.997	0.997	0.998	0.998
Mean of dependent variable	2,311	2,311	2,930	2,930
F-stat. of nonlinear NINO3.4_t vars.		0.40		0.05
F-stat. of nonlinear NINO3.4_{t-1} vars.		1.99		0.27

Notes: The dependent variable is food supply per capita per day (kcal). Each observation is a country-year, and the sample period is 1961-2013. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Standard errors in parentheses are adjusted for spatial correlation (2,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

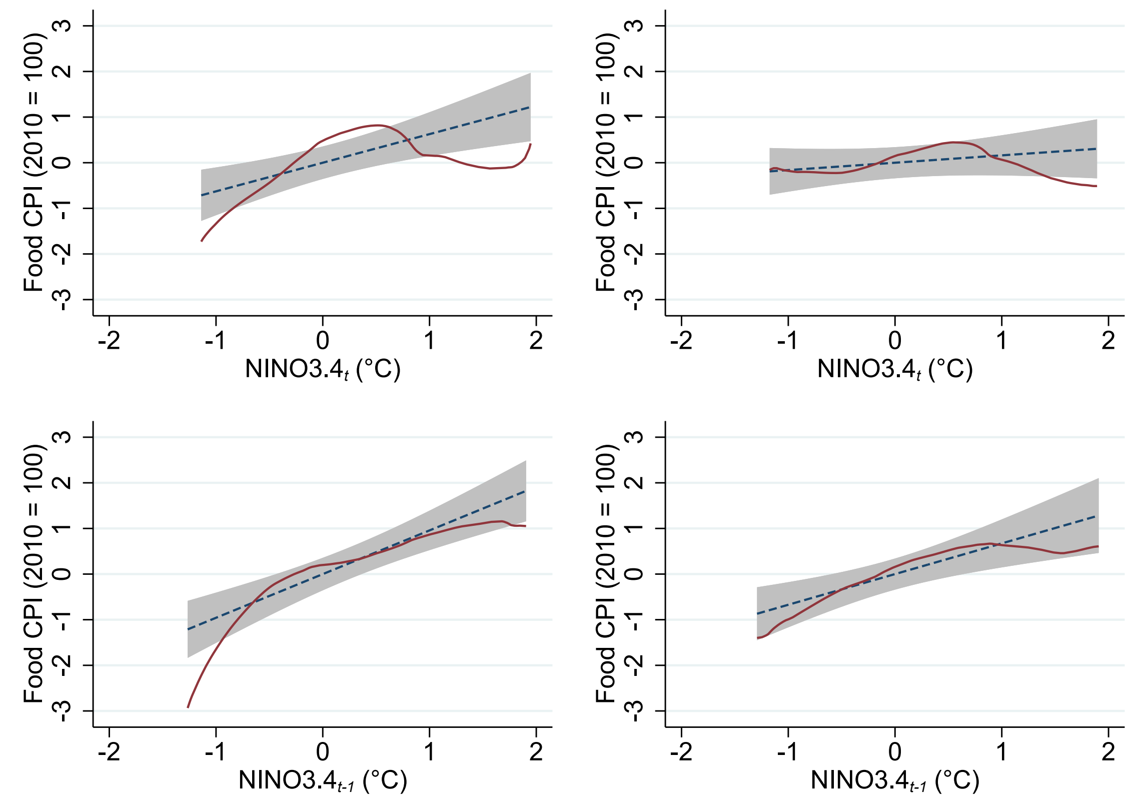
significant at the 0.1 level.

Since there is no strong evidence of a cubic ENSO effect in either country group, the linear model is my preferred specification for analyzing the food supply per capita per day outcome for both groups. (The results from the dummy model specification in Equation 3 are shown for both country groups in Table 10 in Appendix C and Figure 12 in Appendix D.) For both country groups, the linear-model NINO3.4 coefficients in year t and $t-1$ are not significant at the 0.1 level. In summary, I observe no significant ENSO effects on food supply in either country group. These findings are robust to adjusting standard errors for spatial correlation and serial correlation over alternative distances or time lags (Table 11 in

Appendix C), removing country-specific linear trends, or adding country-specific quadratic trends (Table 15 in Appendix C). Even if the observed effects are not due to random error, their magnitudes are small. A +1°C increase in NINO3.4 leads to a combined average loss in years t and $t+1$ of 5.730 kcal per capita per day in ENSO-teleconnected countries, about one-thirteenth of a slice of bread per capita per day; the corresponding gain of 5.230 kcal per capita per day in weakly affected countries is even less.

It is remarkable that I find food supply at the country-year level to be quite stable with respect to ENSO, considering the literature. Iizumi et al. (2014) estimate significant global-mean crop yield anomalies in El Niño years of -4 to 5%, and Hsiang and Meng (2015) find that a 1°C increase in annual NINO3.4 decreases cereal yields and production by 2 to 4% in ENSO-teleconnected countries and increases them by 2% in weakly affected countries on average. Cashin, Mohaddes, and Raissi (2017) and Smith and Ubilava (2017) estimate that El Niño significantly decreases GDP growth by up to 2pp in some ENSO-teleconnected countries and increases it by up to 0.7pp in some weakly affected countries on average. In contrast with these large ENSO effects, the observed stability of food supply implies that, at the country-year level on average, food markets are able to quite successfully smooth ENSO-driven losses and gains in agricultural production over space (through international trade) and time (through food stores) and, despite macroeconomic shocks, retain about the same total demand for food, likely due to relatively inelastic total demand. This is perhaps evidence of "well-functioning" national food markets.

However, the small and insignificant estimated effects on food supply per capita per day may belie larger effects on household nourishment if they are not distributed evenly. If the average loss in ENSO-teleconnected countries due to a +1°C increase in NINO3.4 is accrued by only 20% of a country's population, those individuals lose 28.650 kcal per day; this 20% could perhaps be poorer households or subsistence farmers weakly integrated into larger food markets. If additionally the loss only takes hold during half of the year, perhaps when food stores have run out, the loss is 57.300 kcal per day for those individuals for half of the



(a) ENSO-Teleconnected **(b)** Weakly Affected

Figure 5: Linear Fits of Food Consumer Price Index Against NINO3.4 By Country Group and Period. *Notes:* Linear and nonparametric fits of Food CPI against NINO3.4 in years t and $t-1$ are shown for the ENSO-teleconnected and weakly affected country groups. For each fit, both Food CPI and NINO3.4 in the period of interest are residualized over NINO3.4 of the other period and country-specific fixed effects and linear trends. Linear fits are in dashed blue with shaded 95% confidence intervals using standard errors corrected for spatial correlation (2,000km) and serial correlation (5 years). Nonparametric fits in solid red are local-linear kernel regressions using the Epanechnikov kernel with bandwidth 0.4.

year—about four-fifths of a slice of bread per day. Furthermore, these caloric losses may be more detrimental to individuals who are closer to being under the MDER or are already under it, and the nutritional losses may be more detrimental if the types of foods that are lost are more nutritious. To investigate some of these considerations further, I turn to the food prices and undernourishment outcomes.

4.2 ENSO and Food Prices

Here I analyze ENSO effects on food prices at the country-tropical-year level. I begin again by visually inspecting the linear fits of the ENSO effects. Figure 5 shows linear and non-

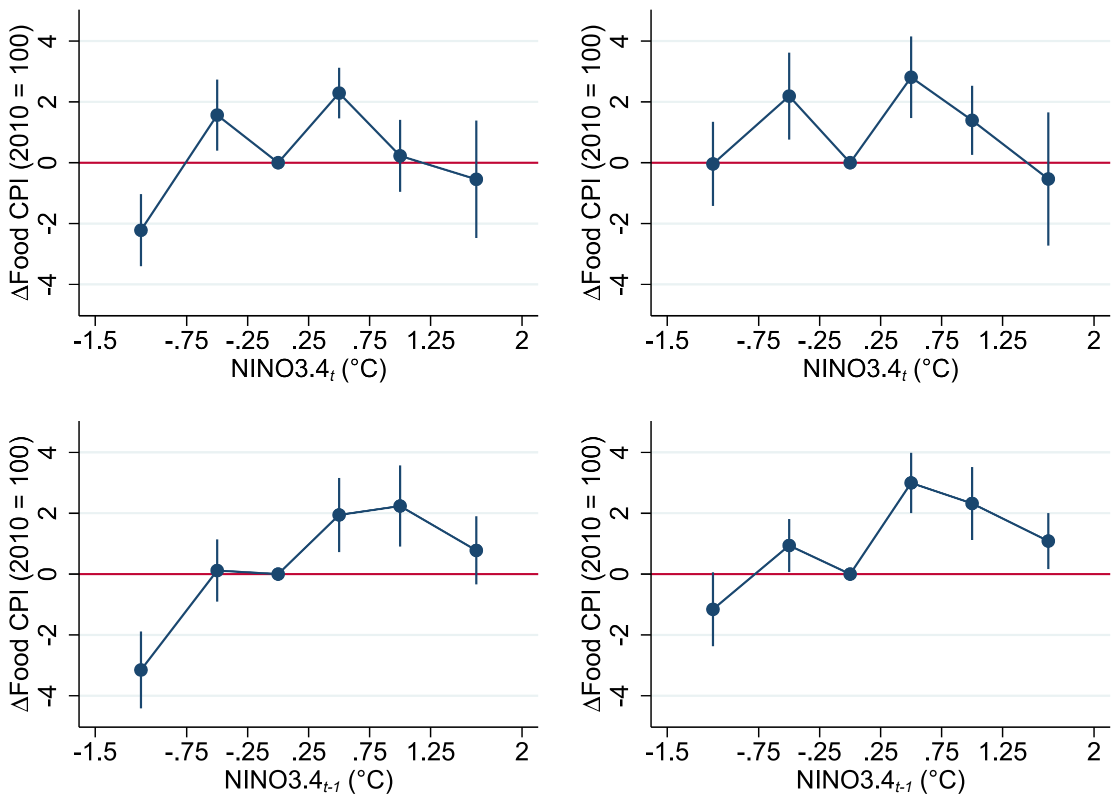
Table 5: Linear and Cubic Regressions of Food Consumer Price Index on NINO3.4 By Country Group

	ENSO-teleconnected		Weakly affected	
	(1) Food CPI	(2) Food CPI	(3) Food CPI	(4) Food CPI
NINO3.4$_t$ (°C)	0.627***	0.692	0.161	0.490
	(0.181)	(0.515)	(0.155)	(0.531)
NINO3.4$_t^2$ (°C)		-1.538***		-0.499
		(0.327)		(0.423)
NINO3.4$_t^3$ (°C)		0.320		-0.0885
		(0.243)		(0.269)
NINO3.4$_{t-1}$ (°C)	0.958***	2.239***	0.672***	1.483*
	(0.176)	(0.500)	(0.194)	(0.884)
NINO3.4$_{t-1}^2$ (°C)		-0.468		-0.194
		(0.433)		(0.549)
NINO3.4$_{t-1}^3$ (°C)		-0.385		-0.323
		(0.332)		(0.513)
Country fixed effects	Yes	Yes	Yes	Yes
Country-specific linear trends	Yes	Yes	Yes	Yes
Observations	1060	1060	1066	1066
Adjusted R^2	0.998	0.998	0.999	0.999
Mean of dependent variable	100.749	100.749	99.445	99.445
F-stat. of nonlinear NINO3.4$_t$ vars.		15.04***		1.92
F-stat. of nonlinear NINO3.4$_{t-1}$ vars.		10.99***		3.19**

Notes: The dependent variable is Food Consumer Price Index (2010 = 100). Each observation is a country-tropical-year, and the sample period is tropical years 2000-2018. NINO3.4$_t$ is the monthly NINO3.4 series averaged over tropical year t. Standard errors in parentheses are adjusted for spatial correlation (2,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

parametric fits as before but for the Food CPI outcome. The plots provide evidence of nonlinearities in ENSO effects: in both the ENSO-teleconnected and weakly affected country groups, a very high NINO3.4 in year t seems to correlate with a Food CPI below that estimated by the linear model. For ENSO-teleconnected countries, a very low NINO3.4 in year t and $t-1$ may be associated with a greater-than-linear decrease in Food CPI.

To test the validity of these suggested nonlinearities, I turn to the estimates of the linear and cubic models in Equations 1 and 2, respectively. Table 5 displays estimates of the two models for both country groups, as well as the F-statistics for the joint significance of the quadratic and cubic NINO3.4 coefficients in years t and $t-1$. For ENSO-teleconnected



(a) ENSO-Teleconnected **(b)** Weakly Affected

Figure 6: Estimated Effects of NINO3.4 on Food Consumer Price Index By Country Group and Period. *Notes:* Coefficients from dummy regressions of Food CPI on NINO3.4 (Table 6) are plotted separately by country group and period. Coefficients estimate effects of NINO3.4 being in the given interval relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. 95% confidence intervals are shown using standard errors adjusted for spatial correlation (2,000 km) and serial correlation (5 years).

countries, the quadratic and cubic coefficients on NINO3.4 in year t and $t-1$ are both significant at the 0.01 level. For weakly affected countries, the quadratic and cubic coefficients on NINO3.4 in year $t-1$ are significant at the 0.05 level.

Since I find strong evidence of a cubic ENSO effect in both country groups, the dummy model specification in Equation 3 is my preferred specification for analyzing the Food CPI outcome for both groups. I present estimates of the dummy model for both country groups in Table 6 and plot the estimated coefficients in Figure 6. A unit increase in the Food CPI is an increase by 1% of 2010 prices, and coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$.

I first describe the estimated effects in ENSO-teleconnected countries. NINO3.4 in year t

Table 6: Dummy Regressions of Food Consumer Price Index on NINO3.4 By Country Group

	ENSO-teleconnected	Weakly affected
	(1) Food CPI	(2) Food CPI
$\text{NINO3.4}_t \in [-1.5, -0.75)$	-2.220***	-0.0390
	(0.604)	(0.705)
$\text{NINO3.4}_t \in [-0.75, -0.25)$	1.567***	2.191***
	(0.595)	(0.728)
$\text{NINO3.4}_t \in [-0.25, 0.25)$	0	0
$\text{NINO3.4}_t \in [0.25, 0.75)$	2.290***	2.809***
	(0.424)	(0.684)
$\text{NINO3.4}_t \in [0.75, 1.25)$	0.226	1.393**
	(0.602)	(0.579)
$\text{NINO3.4}_t \in [1.25, 2.0]$	-0.546	-0.534
	(0.985)	(1.115)
$\text{NINO3.4}_{t-1} \in [-1.5, -0.75)$	-3.153***	-1.159*
	(0.644)	(0.619)
$\text{NINO3.4}_{t-1} \in [-0.75, -0.25)$	0.116	0.940**
	(0.521)	(0.445)
$\text{NINO3.4}_{t-1} \in [-0.25, 0.25)$	0	0
$\text{NINO3.4}_{t-1} \in [0.25, 0.75)$	1.944***	2.997***
	(0.623)	(0.507)
$\text{NINO3.4}_{t-1} \in [0.75, 1.25)$	2.237***	2.323***
	(0.679)	(0.610)
$\text{NINO3.4}_{t-1} \in [1.25, 2.0]$	0.778	1.086**
	(0.570)	(0.468)
Country fixed effects	Yes	Yes
Country-specific linear trends	Yes	Yes
Observations	1060	1066
Adjusted R^2	0.998	0.999
Mean of dependent variable	100.749	99.445

Notes: The dependent variable is Food Consumer Price Index (2010 = 100). Each observation is a country-tropical-year, and the sample period is tropical years 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over tropical year t. Each variable is a dummy for NINO3.4 being in the given interval; coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. Standard errors in parentheses are adjusted for spatial correlation (2,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

in the intervals $[-0.75, -0.25)$, $[0.25, 0.75)$, and $[0.75, 1.25)$ increase Food CPI in year t and $t+1$ on average, with effects being significant at the 0.01 level in at least one period. The combined average effect over years t and $t+1$ for NINO3.4 in year t in $[-0.75, -0.25)$ is +1.683% of 2010 prices, in $[0.25, 0.75)$ it is +4.234% of 2010 prices, and in $[0.75, 1.25)$ it is +2.463% of 2010 prices, all substantial effects on Food CPI. NINO3.4 in year t in $[1.25, 2.0]$ has no significant effects on Food CPI in year t and $t+1$, and the effects are of opposite signs, indicating potential displacement effects. In contrast, I find that NINO3.4 in year t in $[-1.5, -0.75)$ decreases Food CPI in year t and $t+1$ on average, with both effects being significant at the 0.01 level and with a combined average effect of -5.373% of 2010 prices.

In weakly affected countries, a similar pattern emerges. NINO3.4 in year t in the intervals $[-0.75, -0.25)$, $[0.25, 0.75)$, and $[0.75, 1.25)$ increase Food CPI in year t and $t+1$ on average, with all effects being significant at at least the 0.05 level. The combined average effect over years t and $t+1$ for NINO3.4 in year t in $[-0.75, -0.25)$ is +3.131% of 2010 prices, in $[0.25, 0.75)$ it is +5.806% of 2010 prices, and in $[0.75, 1.25)$ it is +3.716% of 2010 prices, all substantial effects on Food CPI. NINO3.4 in year t in $[1.25, 2.0]$ has, on average, an insignificant negative effect on Food CPI in year t and a positive effect of +1.086% of 2010 prices in year $t+1$, significant at the 0.05 level, indicating a delayed or potential displacement effect. These estimated increases for weakly affected countries are larger than those for ENSO-teleconnected countries. Finally, I find that NINO3.4 in year t in $[-1.5, -0.75)$ on decreases Food CPI in year t and $t+1$ by a combined average effect of -1.198% of 2010 prices, with only the year $t+1$ effect significant at the 0.1 level.

In summary, I observe that for ENSO-teleconnected countries, weak and moderate El Niño years and weak La Niña years increase food prices by 2 to 4% of 2010 prices, while strong La Niña years decrease food prices by 5% of 2010 prices, on average. Weakly affected countries follow a similar pattern, with El Niño years and weak La Niña years increasing food prices 1 to 6% of 2010 prices, more so than for ENSO-teleconnected regions, and strong La Niña years decreasing food prices by 1% of 2010 prices, on average. These findings are robust to adjusting standard errors for spatial correlation and serial correlation over alternative distances or time lags (Table 12 in Appendix C) and remain broadly the same after removing country-specific linear trends or adding country-specific quadratic trends (Table 16 in Appendix C).

Interpreting *a priori* what changes in food prices mean for food security is not straightforward, since the prices are determined by both supply and demand shocks. For example, rising food prices may be due to higher costs of procuring food or due to higher demand from increased household incomes. If the former is true, rising food prices make it more difficult for households to purchase food. If the latter is true, rising food prices actually reflect more purchasing of food by households. Indeed, estimated correlations between food prices and food security in other settings are mixed (Alem and Söderbom 2012; Grace, Brown, and McNally 2014; Gregory and Coleman-Jensen 2013). Furthermore, effects of food prices on food security may differ for households that are net producers of food compared to households that are net consumers (Verpoorten et al. 2013). The Food CPI outcome, a measure of average national food prices, may also mask subnational geographic variation in food prices (i.e. urban versus rural areas) or heterogeneity by food type (i.e. greater price effects for more nutritious foods).

In this setting, however, I have additional information on how national food markets respond to ENSO from the previous food supply results and the literature. In ENSO-teleconnected countries, the average increase in food prices caused by El Niño years and the simultaneous, mostly negative El Niño effects on agricultural production (Iizumi et al. 2014; Hsiang and Meng 2015) suggest that the market actions necessary to keep national food supply stable are associated with an increased cost of procuring food, reflected in rising food prices. At the same time, in order for national food supply to remain stable despite rising food prices and mostly negative macroeconomic shocks in El Niño years (Cashin, Mohaddes, and Raissi 2017; Smith and Ubilava 2017), the increased costs are likely absorbed by a relatively inelastic total demand for food. The decrease in food prices due to a strong La

Niña year seems to exhibit this pattern in the reverse direction.

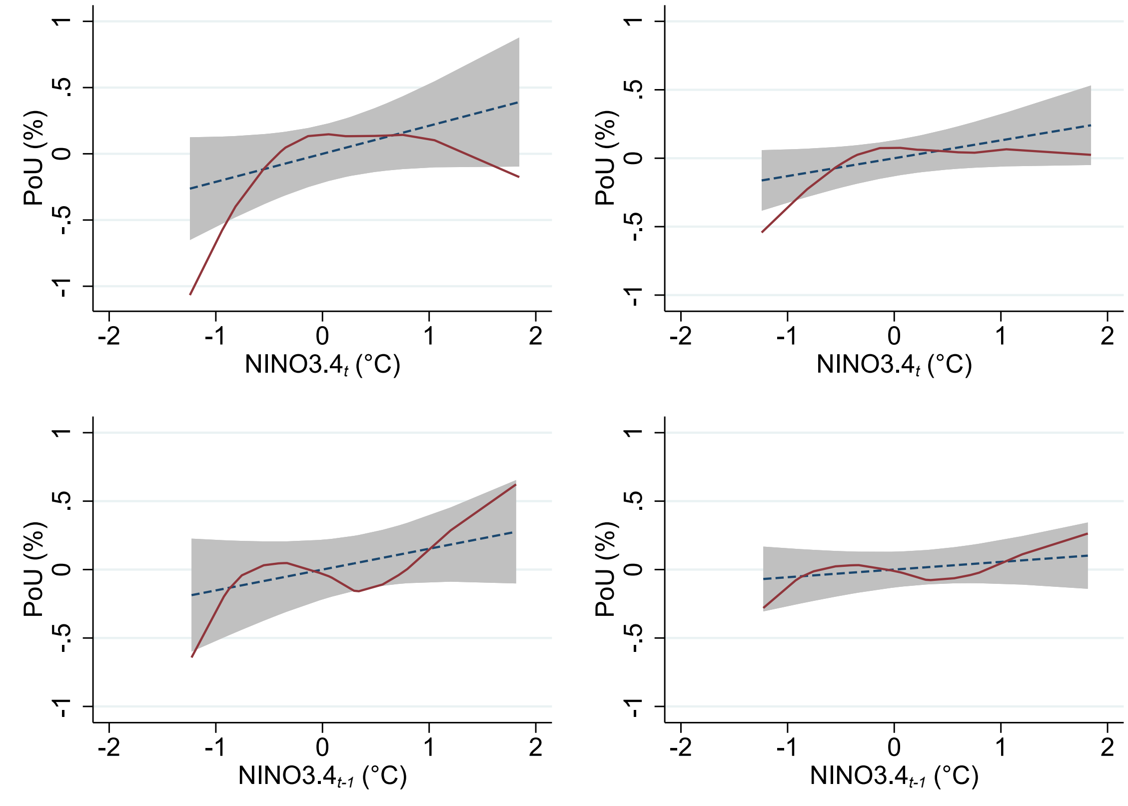
Interestingly, in weakly affected countries, the literature documents weaker, mostly positive El Niño effects on agricultural production (Iizumi et al. 2014; Hsiang and Meng 2015) and weaker, mixed El Niño effects on macroeconomies (Cashin, Mohaddes, and Raissi 2017), yet still, El Niño years increase food prices and strong La Niña years decrease food prices on average, in parallel with the ENSO-teleconnected country group. This suggests spillover or general equilibrium effects on food prices from the ENSO-teleconnected group to the weakly affected group.

This analysis of food markets at the country-year level implies little effect of these food price increases on food security (since food supply is not changing much). However, food price increases may be particularly impactful on the food security of low-income households close to the MDER whose nourishment losses may not make up a large enough portion of total demand to detect in the food supply outcome. In order to further investigate such effects, I turn to the results on the undernourishment outcome.

5 ENSO and Undernourishment

Here I analyze the effects of ENSO on undernourishment at the region-year level. I begin by visually inspecting the linear fits of the ENSO effects. Figure 7 shows linear and nonparametric fits as before but for the prevalence of undernourishment outcome and using standard errors corrected for spatial correlation within 4,000 km and serial correlation over five years. The plots suggest nonlinearities in ENSO effects: for both the ENSO-teleconnected and weakly affected region groups, a very low NINO3.4 in year t appears to be associated with a larger-than-linear decrease in prevalence of undernourishment.

To test the validity of these suggested nonlinearities, I turn to the estimates of the linear and cubic models in Equations 1 and 2, respectively. Table 7 shows estimates of the two models for both region groups, as well as the F-statistics for the joint significance



(a) ENSO-Teleconnected **(b)** Weakly Affected

Figure 7: Linear Fits of Prevalence of Undernourishment Against NINO3.4 By Region Group and Period. *Notes:* Linear and nonparametric fits of prevalence of undernourishment against NINO3.4 in years t and $t-1$ are shown for the ENSO-teleconnected and weakly affected region groups. For each fit, both prevalence of undernourishment and NINO3.4 in the period of interest are residualized over NINO3.4 of the other period and country-specific fixed effects and linear trends. Linear fits are in dashed blue with shaded 95% confidence intervals using standard errors corrected for spatial correlation (4,000km) and serial correlation (5 years). Nonparametric fits in solid red are local-linear kernel regressions using the Epanechnikov kernel with bandwidth 0.4.

of the quadratic and cubic NINO3.4 coefficients in years t and $t-1$. Since these tests are underpowered due to small sample size, the model selection may be biased towards the linear model. Nevertheless, for ENSO-teleconnected regions, the quadratic and cubic coefficients on NINO3.4 in year t are jointly significant at the 0.05 level. For weakly affected regions, the quadratic and cubic coefficients on NINO3.4 in year t and $t-1$ are both not jointly significant at the 0.1 level.

Since I find strong evidence of a cubic ENSO effect in ENSO-teleconnected regions, the dummy model specification in Equation 3 is my preferred specification for analyzing

Table 7: Linear and Cubic Regressions of Prevalence of Undernourishment on NINO3.4 By Region Group

	ENSO-teleconnected		Weakly affected	
	(1) PoU	(2) PoU	(3) PoU	(4) PoU
NINO3.4_t (°C)	0.212*	0.113	0.131*	-0.00849
	(0.125)	(0.349)	(0.0723)	(0.201)
NINO3.4_t^2 (°C)		-0.457**		-0.247**
		(0.195)		(0.118)
NINO3.4_t^3 (°C)		0.164		0.127
		(0.164)		(0.0954)
NINO3.4_{t-1} (°C)	0.152	0.104	0.0561	0.00151
	(0.114)	(0.262)	(0.0683)	(0.177)
NINO3.4_{t-1}^2 (°C)		-0.0409		-0.0616
		(0.255)		(0.142)
NINO3.4_{t-1}^3 (°C)		0.0669		0.0579
		(0.178)		(0.109)
Region fixed effects	Yes	Yes	Yes	Yes
Region-specific linear trends	Yes	Yes	Yes	Yes
Observations	190	190	171	171
Adjusted R^2	0.996	0.997	0.991	0.991
Mean of dependent variable	15.198	15.198	4.828	4.828
F-stat. of nonlinear NINO3.4_t vars.		3.53**		2.28
F-stat. of nonlinear NINO3.4_{t-1} vars.		0.11		0.14

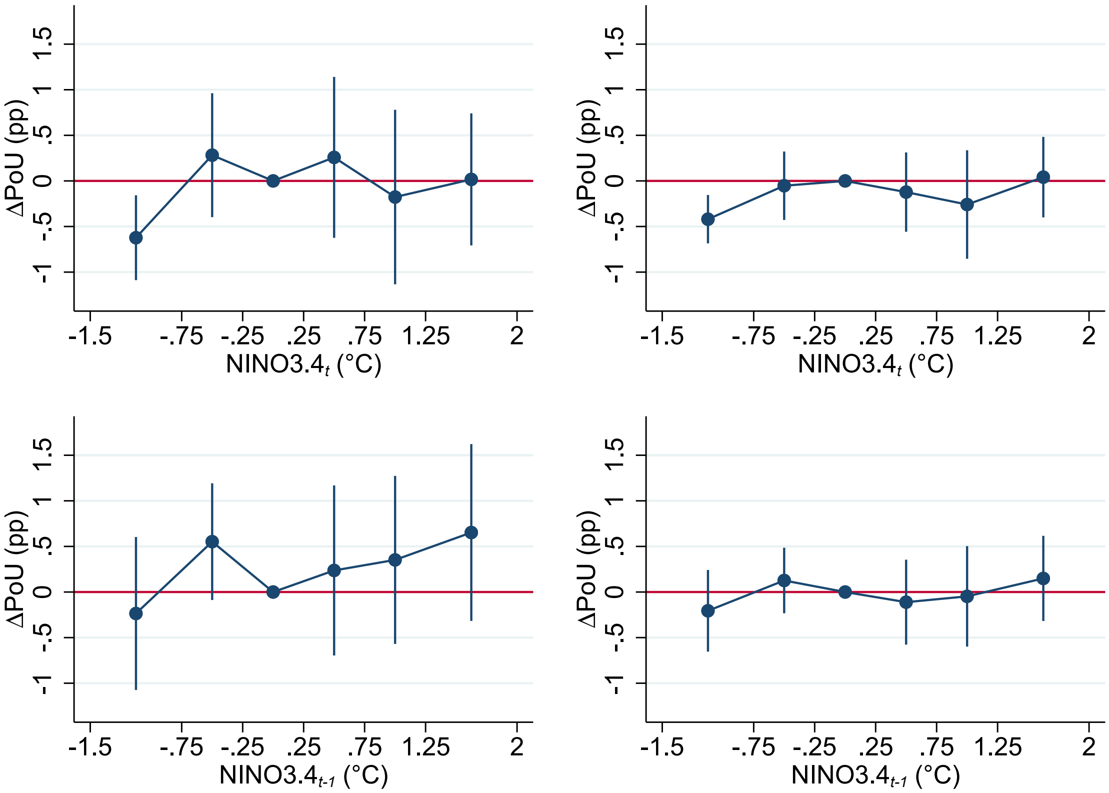
Notes: The dependent variable is prevalence of undernourishment (%). Each observation is a region-year, and the sample period is 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Standard errors in parentheses are adjusted for spatial correlation (4,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the prevalence of undernourishment outcome for this region group. I display estimates of the dummy model for both region groups in Table 8 and plot the estimated coefficients in Figure 8. Since the significance tests for these coefficients are underpowered, I interpret the point estimates as suggestive evidence for ENSO effects on undernourishment. For ENSO-teleconnected regions, NINO3.4 in year t in the intervals $[-0.75, -0.25)$, $[0.25, 0.75)$, $[0.75, 1.25)$, and $[1.25, 2.0]$ increases prevalence of undernourishment in years t and $t+1$ on average, though these effects are not significant at the 0.1 level except for the effect in year $t+1$ of NINO3.4 in year t in $[-0.75, -0.25)$. The combined average effect over years t and $t+1$ for NINO3.4 in year t in $[-0.75, -0.25)$ is +0.834pp, in $[0.25, 0.75)$ it is +0.494pp, in

Table 8: Dummy Regressions of Prevalence of Undernourishment on NINO3.4 By Region Group

	ENSO-teleconnected	Weakly affected
	(1) PoU	(2) PoU
$\text{NINO3.4}_t \in [-1.5, -0.75)$	-0.623***	-0.420***
	(0.236)	(0.134)
$\text{NINO3.4}_t \in [-0.75, -0.25)$	0.282	-0.0528
	(0.344)	(0.190)
$\text{NINO3.4}_t \in [-0.25, 0.25)$	0	0
$\text{NINO3.4}_t \in [0.25, 0.75)$	0.258	-0.123
	(0.447)	(0.220)
$\text{NINO3.4}_t \in [0.75, 1.25)$	-0.177	-0.259
	(0.484)	(0.301)
$\text{NINO3.4}_t \in [1.25, 2.0]$	0.0168	0.0414
	(0.367)	(0.223)
$\text{NINO3.4}_{t-1} \in [-1.5, -0.75)$	-0.235	-0.206
	(0.425)	(0.227)
$\text{NINO3.4}_{t-1} \in [-0.75, -0.25)$	0.552*	0.126
	(0.324)	(0.182)
$\text{NINO3.4}_{t-1} \in [-0.25, 0.25)$	0	0
$\text{NINO3.4}_{t-1} \in [0.25, 0.75)$	0.236	-0.111
	(0.472)	(0.236)
$\text{NINO3.4}_{t-1} \in [0.75, 1.25)$	0.352	-0.0476
	(0.466)	(0.279)
$\text{NINO3.4}_{t-1} \in [1.25, 2.0]$	0.652	0.149
	(0.491)	(0.236)
Region fixed effects	Yes	Yes
Region-specific linear trends	Yes	Yes
Observations	190	171
Adjusted R^2	0.997	0.991
Mean of dependent variable	15.198	4.828

Notes: The dependent variable is prevalence of undernourishment (%). Each observation is a region-year, and the sample period is 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Each variable is a dummy for NINO3.4 being in the given interval; coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. Standard errors in parentheses are adjusted for spatial correlation (4,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.



(a) ENSO-Teleconnected **(b)** Weakly Affected

Figure 8: Estimated Effects of NINO3.4 on Prevalence of Undernourishment By Region Group and Period. *Notes:* Coefficients from dummy regressions of prevalence of undernourishment on NINO3.4 (Table 8) are plotted separately by period and region group. Coefficients estimate effects of NINO3.4 being in the given interval relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. 95% confidence intervals are shown using standard errors adjusted for spatial correlation (4,000 km) and serial correlation (5 years).

$[0.75, 1.25)$ it is +0.175pp, and in $[1.25, 2.0]$ it is +0.669pp, all sizable increases in prevalence of undernourishment. In contrast, for a very low NINO3.4 in year t in $[-1.5, -0.75)$, the combined average effect is -0.858pp, a large reduction in prevalence of undernourishment, with the effect in year t being significant at the 0.01 level.

Since I find no strong evidence of a cubic ENSO effect in weakly affected regions, the linear model is my preferred specification for analyzing the prevalence of undernourishment outcome for this region group. For weakly affected regions, a +1°C increase in NINO3.4 in year t increases prevalence of undernourishment by +0.187pp combined over years t and $t+1$ on average, with only the effect in year t significant at the 0.1 level.

In summary, I find that for ENSO-teleconnected regions, El Niño years and weak La Niña years may increase undernourishment by 0.2 to 0.8pp, while strong La Niña years reduce undernourishment by 0.9pp, on average. Undernourishment in weakly affected regions is less affected by ENSO, with El Niño years increasing undernourishment by 0.1 to 0.3pp and La Niña years decreasing it by 0.1 to 0.2pp on average. These findings are robust to adjusting standard errors for spatial correlation and serial correlation over alternative distances or time lags (Tables 13 and 14 in Appendix C) and remain broadly the same after removing country-specific linear trends or adding country-specific quadratic trends (Table 17 and 18 in Appendix C). Furthermore, these estimated effects on prevalence of undernourishment, the extensive margin of undernourishment, may be accompanied by effects on the intensive margin for undernourished households. It is plausible that as more households fall below the MDER, households already under the MDER also face a reduction in food security. If this is true, the implied food security effects due to changes in prevalence of undernourishment are even greater.

That I observe ENSO effects on undernourishment despite finding little effect on food supply shows that while national food markets are able to supply virtually the same amount of food per capita, this masks significant food losses or gains for certain households, particularly those close to the MDER. Mechanisms by which El Niño increases undernourishment may be through increased food prices, as observed previously; decreased incomes of vulnerable households, particularly likely in ENSO-teleconnected regions (Cashin, Mohaddes, and Raissi 2017; Smith and Ubilava 2017); reduced harvests for subsistence farmers weakly integrated into larger food markets; or decreased physical access to food markets.

I investigate the food prices channel. Comparing ENSO effects on undernourishment to those on food prices reveals striking similarities. For the ENSO-teleconnected country and region group, an El Niño or weak La Niña year causes an increase in food prices and may also increase undernourishment. A strong La Niña year decreases food prices and also decreases undernourishment. This implies that increasing (decreasing) food prices are an important factor pushing marginally-undernourished households below (above) the MDER.

For the weakly affected country and region group, there is a similar but weaker correspondence. An El Niño or weak La Niña year causes an increase in food prices but causes small and mixed effects on undernourishment. A strong La Niña year decreases food prices and undernourishment, but less so than for the ENSO-teleconnected group. This implies that ENSO-driven effects on food prices have smaller associated effects on undernourishment for the weakly affected group than for the ENSO-teleconnected group, which may be thanks to higher average household incomes in weakly affected countries and regions allowing households to generally better absorb food price shocks or stronger welfare support from governments in these countries.

6 Conclusion

Food security has been suggested to be linked to the global climate, but past literature has only focused on the effects of local weather conditions, inadequate analogs for global climate variables.

Here, I study the effects on food security of ENSO, a dominant mode in the global climate. I match a continuous ENSO index with panel data on three food security outcomes—food supply and food prices at the country level, which together summarize national food markets, and undernourishment at the regional level. I separate countries and regions into ENSO-teleconnected and weakly affected groups and estimate average within-country or within-region ENSO effects on the three outcomes separately for these two groups.

Looking first at national food markets, I find that ENSO has small and insignificant effects on food supply at the country-year level in all countries on average. In contrast with documented, negative ENSO effects on agricultural production and macroeconomies, the stability of food supply implies that national food markets are able to smooth these ENSO effects over space and time. However, I also find that ENSO deviations from the neutral state increase food prices in all countries on average, presumably due to the market actions required to maintain stable food supply, with the exception of strong La Niña years, which decrease food prices on average. The parallel between ENSO-teleconnected and weakly affected countries also implies that the food price effects spillover from ENSO-teleconnected to weakly affected countries.

Turning to undernourishment, I find that ENSO deviations from the neutral state may increase undernourishment in ENSO-teleconnected regions, with the exception of strong La Niña years, which decrease undernourishment, while warmer ENSO states weakly increase undernourishment in weakly affected regions, on average. This shows that the observed stability in food supply belies significant food losses for certain vulnerable households, particularly in ENSO-teleconnected regions. The parallel between ENSO effects on food prices and undernourishment suggests that changing food prices play a role in ENSO-driven undernourishment and more so for ENSO-teleconnected regions. Taken together, the results identify ENSO to be a significant factor in the stability of food access but not food availability; ENSO-driven instabilities in food security look not like massive food shortages but rather like food price fluctuations that affect the nourishment of vulnerable households, particularly in ENSO-teleconnected areas.

The results from this study have several policy implications. First, given the predictability of ENSO (Chen and Cane 2008), they provide estimates for policymakers and households to forecast effects on food security outcomes. This could help policymakers target food security policy and households smooth undernourishment and food price shocks over time. Second, the results suggest that, at the national level, food subsidies may be a more effective policy tool to address ENSO-driven food insecurity than food aid, since national food supplies are stable but food prices are not and are correlated with undernourishment. If externally valid, the results may more broadly suggest that shocks to national food markets from any cause (similar enough to ENSO) may be better addressed through food subsidies than through food aid. Third, the implicated spillover or general equilibrium ENSO effects on food prices from ENSO-teleconnected to weakly affected countries mean that food security policy in ENSO-teleconnected countries may be relevant to weakly affected countries. Finally, if the effects of ENSO are externally valid to predict the effects of global warming, another global climate condition similar in many ways to ENSO, the results imply that global warming may have associated increases in undernourishment and food prices. These effects may be incorporated into projected costs of global warming scenarios.

Further research using more disaggregated and country-specific data would help solidify findings and improve the accuracy of food-security forecasts. Investigation of the heterogeneities in ENSO effects on food security by country average income (as in Hsiang, Meng, and Cane (2011)) or openness to trade may uncover valuable patterns. Finally, more research on the mechanisms through which ENSO affects undernourishment and food prices could find ways to mitigate these ENSO-driven instabilities.

Appendix A Background

A.1 Global Food Security

The FAO defines food security as "a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, IFAD, UNICEF, WFP and WHO 2019). Four sequential dimensions of food security follow from this definition (Pinstrup-Andersen 2009). The first is *availability*–whether the market for food supplies enough total food for a given population. This encompasses the capacity of the food market (agricultural producers and food reserves) to meet not the total economic demand for food but the total nutritional demand for food, which could theoretically be higher or lower (Schmidhuber and Tubiello 2007). If ample food supply is available, the second dimension is whether consumers (individuals) have adequate *access* to it, both physical and economic. In particular, consumer budget constraints, trade-offs to purchasing food, agricultural production costs, price markups, and various market frictions can hinder consumers' acquisition of a nutritiously-adequate amount of food. Note that individuals may be net consumers or net producers of food (farmers), though most individuals are net consumers (Tweeten 1999). Thirdly, if individuals have access to enough food, the dimension of *utilization* considers whether individuals properly intake the nutrients and energy from the food. While this occurs after the market transaction for food, it requires sufficient access to complementary goods such as nutritional education, good health, sanitation, and food preparation paraphernalia. Finally, the fourth dimension is the *stability* of food availability, access, and utilization in the face of climatic, economic, political, or social supply- and demand-side shocks. This includes, for example, the stability of food prices and the ability of individuals to smooth food consumption over time through food stores, insurance, or other devices. Food insecurity, then, is the failure of one or more of these dimensions of food security. In the present study, I investigate the dimension of stability of food availability and access in the face of supply- and demand-side shocks caused by ENSO.

The right to food has been widely considered a fundamental human right since its inclusion in the Universal Declaration of Human Rights in 1948 (United Nations 1948) and in the United Nations Sustainable Development Goal of ending hunger and achieving global food security by 2030 (Rosa 2017). Thus, some see the provision of food as an end in itself (Mechlem 2004).

Food insecurity has also been shown to negatively impact various health and quality-of-life outcomes. Food insecurity is associated with decreased consumption of fruits, vegetables, potassium, fiber, and vitamin C among mothers in rural New York (Kendall, Olson, and Frongillo 1996) and with low and high body mass index among Finnish adults (Sarlio-Lähteenkorva and Lahelma 2001). Food-insecure children report poorer health, are more likely to have asthma, and have compromised psychosocial functioning (Olson 1999), while food-insecure seniors face limitations in daily activities, in the United States (Gundersen and Ziliak 2015). Food insecurity has been suggested to increase the incidence of chronic diseases such as diabetes as well as levels of stress, anxiety, and depression in pregnant women (Lee et al. 2012). Access to healthcare is also negatively associated with food insecurity, with food-insecure Americans being more likely to postpone medical care and use acute care (Kushel et al. 2006). Finally, food-insecure individuals in Canada bemoan the monotony of their diets and feelings of alienation (Hamelin, Beaudry, and Habicht 2002).

Food insecurity may have large economic costs due to decreased labor productivity and labor force participation of malnourished individuals and from increased associated healthcare costs. Horton and Steckel (2011) estimate that inadequate nutrition is associated with a loss of as much as 12% of GDP in poor countries. Fink et al. (2016) find that stunting (having a low height-for-age) during childhood costs developing countries $616.5 billion per cohort, while Hoddinott et al. (2013) estimate that a one-fifth reduction in stunting leads to an 11% income gain on average. Meanwhile, obesity was estimated to cost 2.8% of global GDP in 2014 (Tremmel et al. 2017) and up to 20% of healthcare expenditures in the United States in 2005 (Lehnert et al. 2013).

The prevalence of undernourishment of world regions over the last 20 years is shown in

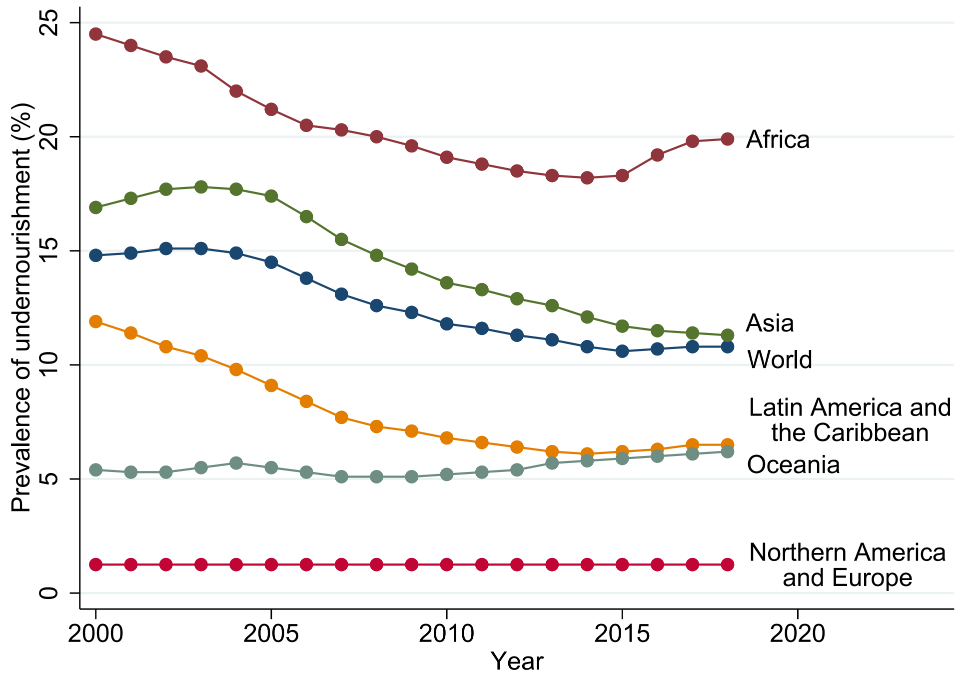


Figure 9: Annual Prevalence of Undernourishment Series By World Region. *Notes:* Data are from the Food Insecurity Indicators dataset in the FAOSTAT database (FAO 2019).

Figure 9 using data from the Food Insecurity Indicators dataset in the FAOSTAT database (FAO 2019). Despite considerable reductions in undernourishment over the last 20 years, a substantial level of undernourishment prevails around the world, especially in Africa and Asia, and the prevalence of undernourishment has seen an uptick since 2015 in Africa, Latin America and the Caribbean, Oceania, and the world average.

A.2 Causes of Food Insecurity

A set of literature has focused on identifying causes of food insecurity. These studies often implicitly focus on one dimension of food security, usually availability, access, or the stability of these two. Many of the causes of food insecurity could plausibly be caused by food insecurity (i.e. unemployment) or some confounding variable (i.e. health), and most of these studies lack exogenous variation in the explanatory variable and thus offer only correlational evidence. Nevertheless, they shed light on some of the potential determinants of food insecurity.

One strand of the literature has identified climatic and environmental factors as causes of food insecurity. Qualitative research suggests these factors to be important determinants. Misselhorn (2005) finds that among local-level case studies across southern Africa, climate and environmental stressors were the most commonly cited "direct" driver of food insecurity and the second most commonly cited "underlying" driver. Based on ethnographic surveys in Nigeria, Sudan, South Africa, and Mexico, trends in precipitation were ranked one of the "most important" determinants of food insecurity and droughts "very important" (Ziervogel et al. 2006). Among surveyed households in northern Bangladesh, 90% reported negative effects of rainfall variability on food security through reductions in subsistence production or through increased food prices (Etzold et al. 2014). A few quantitative analyses corroborate these findings in the rural African setting where most households are smallholders. In rural Ethiopia, higher annual rainfall levels are associated with higher household food security, and rainfall deviations from the long-run mean are weakly associated with lower household food security (Demeke, Keil, and Zeller 2011). In rural Kenya, wet seasons are associated with a 2 to 11 kcal increase in daily food consumption of households (Nyariki, Wiggins, and Imungi 2002). Finally, in rural South Africa, households that reported losing most or all of their crop due to poor rainfall or hailstorms consumed 21% to 48% less food in monetary value on average (Tibesigwa et al. 2016).

Previous research has also documented the relationship between food insecurity and various aspects of the macroeconomy. High-poverty countries have higher prevalence of children underweight than low-poverty countries on average (Smith, Obeid, and Jensen 2000). In EU countries following the Great Recession, rising unemployment rates and declining average wages were associated with increasing prevalence of food insecurity (Loopstra et al. 2016). In the United States, state poverty and unemployment rates are positively correlated with prevalence of food insecurity (Dharmasena, Bessler, and Capps 2016). These patterns are also observed at the household level. In the United States, households with lower incomes and fewer physical and financial assets are more likely to be food insecure (Gundersen and Ziliak 2018). In rural Nicaragua, households with off-farm employment and larger farms have shorter seasonal hunger on average (Bacon et al. 2017). In rural Ethiopia, ox ownership and farmland size are positively correlated with food security (Kidane, Alemu, and Kundhlande 2005). In rural Kenya, off-farm earnings are positively correlated with food security (Nyariki, Wiggins, and Imungi 2002). Food prices have also been shown to be correlated with food security. As Sub-Saharan Africa faced rising food prices from 2005 to 2008, self-reported food security improved for rural households and worsened for urban households on average (Verpoorten et al. 2013). In the same period, another study finds that household food consumption in Ethiopia decreased on average, particularly strongly for households with few assets and for casual workers (Alem and Söderbom 2012). In Kenya, higher local maize prices are correlated with reduced low birth weight of infants (Grace, Brown, and McNally 2014). In the United States, households in the Supplemental Nutrition Assistance

Program are more likely to be food insecure in areas with higher food prices (Gregory and Coleman-Jensen 2013), and perhaps similarly, low-income households are more likely to be food insecure during seasons of high heating or cooling costs (Nord and Kantor 2006). One study argues that civil conflict is a cause of food insecurity (Messer and Cohen 2007).

A.3 The El Niño-Southern Oscillation

El Niño climate phenomena are oceanic warming events that occur in the tropical Pacific Ocean and consist of an increase in sea surface temperature (SST) and a weakening of equatorial trade winds (Timmermann et al. 2018; Wang et al. 2017). These two occurrences mutually reinforce each other through the Bjerknes feedback mechanism: a rise in SST in the eastern tropical Pacific decreases the east-west Pacific SST gradient, reducing equatorial trade winds, which further reinforces the SST rise. This warming of the tropical Pacific Ocean generates atmospheric waves that propagate the warming around the globe and affect local climate conditions in so-called ENSO-teleconnected areas throughout the tropics and extratropics (Chiang and Sobel 2002). El Niño events typically begin in boreal spring, when the tropical Pacific experiences low cloud cover and high solar insolation, grow in intensity through the summer and fall, and reach maturity in the winter, after which they decay rapidly in late winter and spring.

La Niña phenomena, on the other hand, are oceanic cooling events in the tropical Pacific Ocean, reinforced by Bjerknes feedback in the opposite direction, that also impact the global climate, in generally opposite ways to El Niño (Timmermann et al. 2018; Wang et al. 2017). La Niña events usually follow the decay of El Niño events and mature by the following winter. However, La Niña events tend to involve smaller deviations in SST than El Niño events and last longer, up to several years. The repeated shifting of the tropical Pacific Ocean between El Niño and La Niña phases is known as the El Niño-Southern Oscillation (ENSO) and has a period of three to seven years. ENSO has been occasionally studied by economists and deserves attention in the study of the global climate and food security for several reasons.

Firstly, ENSO is the strongest source of interannual fluctuation in the global climate system (Timmermann et al. 2018) (other noteworthy interannual patterns in the global climate system include the North Atlantic Oscillation, the Pacific Decadal Oscillation, and the Atlantic Multidecadal Oscillation (Hsiang and Kopp 2018)). Its large geographical reach makes it an important mode for many regions of the globe, especially those with high prevalence of food insecurity.

Secondly, ENSO is the most predictable interannual fluctuation in the global climate system (Chen and Cane 2008), although the limits of its predictability due to inherently stochastic mechanisms remain a subject of debate (Timmermann et al. 2018). For example, Chen et al. 2004 predict all significant El Niño events in a 148-year period with lead times of up to two years. ENSO prediction has become routine practice at climate centers worldwide, such as the Climate Prediction Center of the National Oceanic and Atmospheric Administration (Climate Prediction Center Internet Team 2009). While ENSO forecast models have plateaued at moderate levels with only gradual improvement in the past couple decades (Clarke 2014), there is evidence for potential improvement in the future (Chen and Cane 2008). The predictability of ENSO means that the elucidation of its effects on food insecurity could help governments and agencies predict year-to-year trends in food security.

How ENSO will respond to global climate change remains uncertain and an important and active area of research (Timmermann et al. 2018). Some climate models project intensification of ENSO (Power et al. 2013), and while the occurrence of exceptionally strong El Niño events in recent years (1982-83, 1997-98, and 2014-16) suggests so, these trends are not unprecedented (Cobb et al. 2013; Wolter and Timlin 2011). Whatever the effect of climate change on ENSO, it is expected to remain a dominant mode in the global climate in the future, so it remains relevant to study (Wang et al. 2017).

Finally, Hsiang, Meng, and Cane 2011 argue that studying ENSO is preferable to using local temperature or rainfall shocks as analogs for changes in the global climate for several reasons. The global climate system may affect socioeconomic outcomes through channels other than temperature or rainfall; studying ENSO directly accounts for additional channels. Furthermore, the effect of local weather shocks may be different from the effect of planetary-scale, correlated weather shocks that are present in the current global climate system, which global climate change exemplifies. Lastly, the effect of predictable climate changes on socioeconomic outcomes may be different from unpredictable shocks.

A.4 Global Effects of ENSO

ENSO exhibits a teleconnection pattern that affects local climates in ENSO-teleconnected areas throughout the tropics and extratropics. Warm ENSO periods are strongly associated with warmer surface temperatures in Central America, central and west coast South America, northwest North America, southeast Asia, southeast Africa, and central Australia, while cold ENSO periods strongly correspond to colder surface temperatures in Central America, central and west coast South America, northwest North America, western Europe, southeast Asia, and Africa (Halpert and Ropelewski 1992; Trenberth and Caron 2000). El Niño episodes are strongly associated with higher precipitation levels in central Pacific, eastern Africa, and southeastern South America, and with lower precipitation levels in western Pacific,

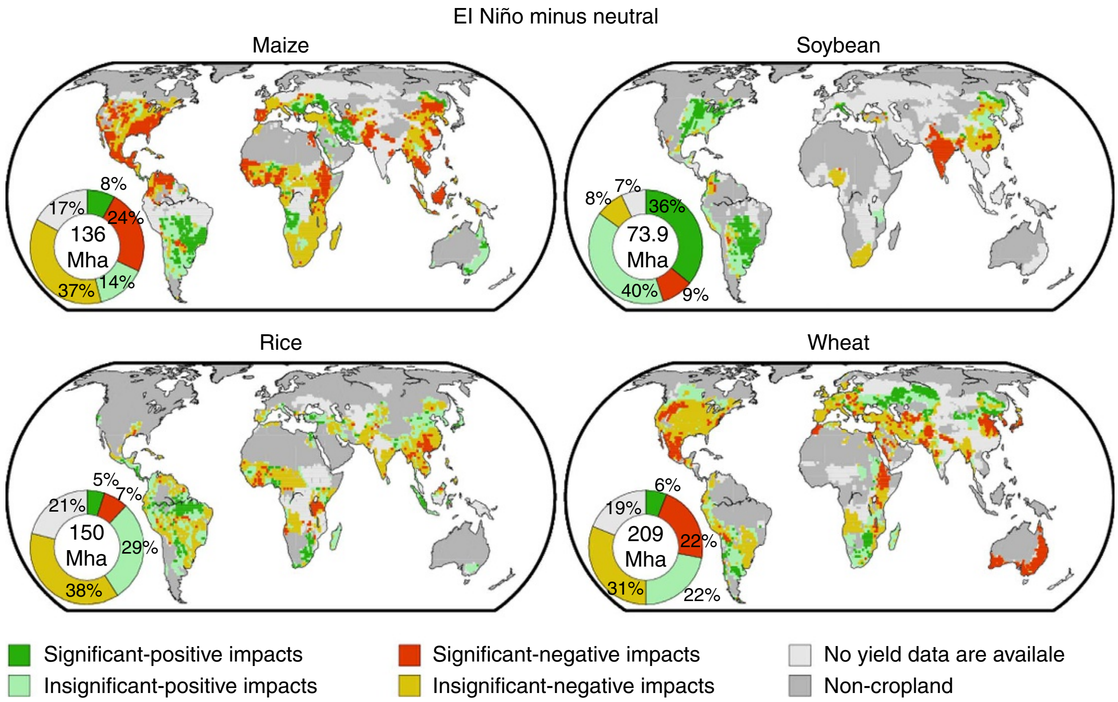


Figure 10: Crop Yield Anomalies in El Niño Years By Crop. *Notes:* The maps color cropland pixels with their estimated yield anomalies in El Niño years from a 5-year running mean for four crops. The significance level is 0.1, and standard errors are bootstrapped. The pie diagrams indicate the distribution of yield anomalies among global harvested area in 2000. Reproduced from Iizumi et al. (2014).

Australia, southern Asia, southeast Africa, northeastern South America, and the Caribbean, with median precipitation shifts on the order of 20 percentile points (C. F. Ropelewski and M. S. Halpert 1987; Chester F. Ropelewski and Michael S. Halpert 1996; Trenberth and Caron 2000). For a sense of magnitudes, Hsiang and Meng (2015) estimate that a 1°C increase in NINO3.4 is associated with a 0.27°C temperature increase and 4.64 mm/month precipitation decrease in tropical countries, while it is associated with a 0.13°C temperature decrease in temperate countries. In addition, tropical cyclones in the North Pacific tend to be more intense and longer-lived in El Niño years (Camargo and Sobel 2005), hurricanes in the North Atlantic are more common during La Niña years (Donnelly and Woodruff 2007), and higher ENSO variation is associated with more coastal erosion on the Pacific Ocean basin (Barnard et al. 2015).

These ENSO-driven, local-climatic changes translate into various significant effects on human societies around the globe. While the main channels of these effects are expected to be due to changes in local temperature and precipitation, there may be other documented or undocumented climatic channels that affect social and economic variables. The following cited studies account for all potential channels of ENSO effects by indexing the oscillation itself.

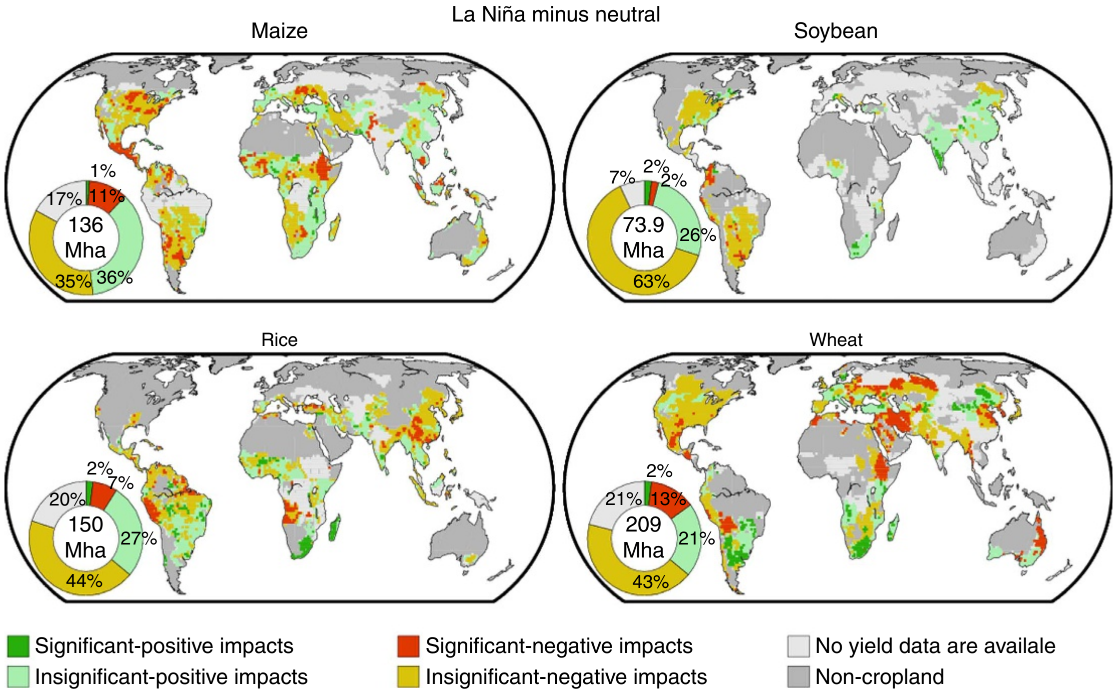


Figure 11: Crop Yield Anomalies in La Niña Years By Crop. *Notes:* The maps color cropland pixels with their estimated yield anomalies in La Niña years from a 5-year running mean for four crops. The significance level is 0.1, and standard errors are bootstrapped. The pie diagrams indicate the distribution of yield anomalies among global harvested area in 2000. Reproduced from Iizumi et al. (2014).

Firstly, ENSO is found to have a significant impact on agricultural yields and production around the globe. Iizumi et al. (2014) estimate significant maize, soybean, rice, and wheat yield anomalies in both El Niño and La Niña years for many regions of the world, mapped in Figures 10 and 11, respectively. The effects vary by region, but Iizumi et al. (2014) estimate that El Niño years increase the global-mean soybean yield by 2.1 to 5.4% and the global-mean maize, rice, and wheat yields by -4.3 to +0.8%, while La Niña years decrease the global-mean yields of all four crops by 0 to 4.5%, on average. Hsiang and Meng (2015) find that a 1°C increase in NINO3.4 lowers cereal yields by 2% and total cereal production by 3.5% for ENSO-teleconnected countries but raises cereal yields by 1.7% and total cereal production by 2.4% for weakly affected countries on average. These global-level studies are corroborated by those at the regional or country levels, which also highlight heterogeneity in ENSO effects depending on location, crop, and growing season. El Niño events tend to decrease rice production in Indonesia with considerable variation by region (Falcon et al. 2004), and they tend to decrease rice production in the Philippines only in the dry season and more so for rainfed systems than irrigated ones (Roberts et al. 2009). Meanwhile, ENSO has little effect on Chinese rice production because most of its effects occur outside of growing season with little temperature effect (Deng et al. 2010). El Niño phases decrease rice and wheat production in India on average, but not that of sorghum and chickpea (Selvaraju 2003). In the southeastern United States, maize, tomato, sugarcane, and rice yields are linked to ENSO with substantial heterogeneity by crop and region (Hansen et al. 2015), while in eastern Argentina, El Niño events are associated with higher maize and sorghum yields but not soybean and sunflower yields (Podestá et al. 1999). El Niño events are negatively correlated with, and La Niña events positively correlated with, maize yields in Zimbabwe (Cane, Eshel, and Buckland 1994). These documented effects on agricultural production have considerable impact on the income of the agricultural sector. Hsiang and Meng (2015) estimate that a 1°C increase in NINO3.4 decreases agricultural income by 1.8% for tropical countries but increases it by 1.6% for temperate countries on average. Selvaraju (2003) corroborates this pattern for the Indian case with losses in El Niño years and gains in La Niña years on average, and Adams et al. (1999) also finds this pattern in the United States with losses in El Niño years but worse losses in La Niña years on average.

ENSO has also been found to affect the macroeconomy as a whole. Cashin, Mohaddes, and Raissi (2017) find that a standard-deviation El Niño shock decreases GDP growth in Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa by 0.5 to 2.5pp, while it increases GDP growth in the United States, Europe, and China by 0.5 to 0.7pp, on average. Similarly, Brunner (2002) finds that a standard deviation El Niño shock increases GDP growth in G-7 countries by 0.5pp on average, though weakly significantly. Smith and Ubilava (2017) find a 1 to 2pp reduction in economic growth on average due to a 1°C increase in NINO3.4 for developing countries, with effects twice as large for tropical areas than temperate areas. In the case of the United States, Berry and Okulicz-Kozaryn (2008) find no evidence of ENSO effects on economic growth, but Changnon (1999) estimates net economic benefit following the 1997-98 El Niño thanks to reductions in heating costs and record home sales. In other parts of the world, the 1998 El Niño was estimated to decrease economic activity in Seychelles's tuna industry (Robinson et al. 2010), and the 1991 El Niño was found to depress incomes in rural Indonesia on average (Salafsky 1994). ENSO has also been shown to affect prices. Cashin, Mohaddes, and Raissi (2017) estimate an 8% increase in non-fuel commodity prices two quarters after a standard deviation ENSO shock, while Brunner (2002) estimates a 3.5 to 4pp increase in the inflation, on average. El Niño events tend to increase world rice prices (Falcon et al. 2004) and world prices of coffee from southeast Asia and Oceania but decrease world prices of coffee from South America and West Africa (Ubilava 2012).

Finally, ENSO has been linked to human health and conflict. El Niño is associated with malaria epidemics in India and parts of South America and east Africa (Kovats et al. 2003; Hales, Edwards, and Kovats 2003; Patz et al. 2005). In the South Pacific, dengue fever epidemics are caused by La Niña, while they are associated with El Niño in southeast Asia and parts of South America. Furthermore, El Niño is associated with Rift Valley Fever in east Africa, rodent-borne diseases in the United States, and diarrhoeal diseases in Peru and Bangladesh. Turning to human conflict, civil conflict onset is found to be associated with El Niño years for tropical countries but not for temperate ones (Hsiang, Meng, and Cane 2011).

Appendix B Data Description

B.1 Food Supply Data

I use the variable food supply per capita per day measured annually at the country level from 1961 to 2013 from the historical Food Balance Sheets dataset in the FAOSTAT database (FAO 2019). FAOSTAT also has a Food Balance Sheets dataset covering 2014 to 2017 using a new methodology, but these data were omitted from the study due to comparability concerns. Starting with country-reported official statistics on about 100 food items covering most crop and livestock products (primary commodities and some processed commodities; for example, apples, beef, and maize), the FAO computes the total quantity of foodstuffs in a country-year as the sum of the quantity produced in that country, the quantity imported, and the net change in stocks during the year. From this total quantity of foodstuffs is subtracted the quantity exported, fed to livestock, used for seed, put to manufacture, and lost due to storage and transportation, leaving an estimate of food supply available for human consumption. The food supply is converted to dietary value by applying caloric composition factors to the distribution of food items supplied and is divided by the country's population and the number of days in a year to provide a measure of the average number of calories available to every person every day in a given country-year.

The FAO warns that data quality varies between countries since the food supply per capita per day measure is based on official statistics reported by countries and not routinely assessed for quality, and some data on food production and trade are imputed. Therefore, the FAO cautions that geographical and temporal comparability over longer time periods are limited, though comparability over shorter time periods is reasonably good. In all regression analyses using this data, I only estimate within-country effects, circumventing limitations in geographic comparability, and I include country-specific linear trends to control for limited comparability over longer time periods.

B.2 Food Prices Data

I use the variable Food Consumer Price Index (Food CPI) measured at the country level monthly from January 2000 to July 2019 from the Consumer Price Indices dataset in the FAOSTAT database (FAO 2019). The Food CPI data series are based on household survey data reported by countries and compiled by the International Labor Organization until 2014 and thereafter by the International Monetary Fund (IMF) and the United Nations Statistics Division (UNSD), with additions from various statistical offices for historical data for certain countries. The Food CPI measures the nominal price level of an average basket of food and beverages purchased by households as a percentage of the price level in the reference period. The reference period for all country series is set to the year 2010 using each country's geometric mean of monthly Food CPIs in 2010 as the rescaling factor. I divide each Food CPI country series by the general Consumer Price Index country series with reference period 2010, also from the Consumer Price Indices dataset, to obtain a measure of the real price level of an average basket of food and beverages in each country as a percentage of the price level in 2010.

Since household survey data are reported by countries, the FAO warns that differences in data collection quality between countries limits cross-country comparability. Cross-country comparability is also limited due to differences in statistical methodology: some countries sample households in urban areas only, countries vary in terms of expenditure weights used and the frequency of their update, and there are differences in countries' product coverage and index aggregation formulas. As with the food supply outcome, in all regression analyses using this data, I only estimate within-country effects using time series variation, avoiding cross-country comparisons; reassuringly, the source data is processed by the IMF and UNSD to ensure comparability over time within each country.

B.3 Undernourishment Data

I use the variable prevalence of undernourishment (PoU) computed at the country-aggregated regional level annually from 2000 to 2018 from the Food Security Indicators dataset in the FAOSTAT database (FAO 2019). The PoU estimates the percentage of the population whose dietary energy intake is below the Minimum Dietary Energy Requirement (MDER) necessary for normal and healthy living and is the main indicator used by the FAO to track macro-level trends in food insecurity. While the FAO does compute the PoU at the country level for three-year averages, in this study I use the PoU series at the country-aggregated regional level (a population-weighted average of its countries) computed annually in order to temporally isolate the effects of annual ENSO shocks. The PoU is a parametric-model-based indicator currently based on three parameters: (1) the average dietary energy consumed by the population (the previously described food supply outcome from the Food Balance Sheets dataset); (2) the coefficient of variation representing the variability of dietary energy consumption in the population; and since 2011, (3) the degree of skewness in the distribution of dietary energy consumption; the latter two parameters are estimated from household surveys. The probability distribution of dietary energy consumption is modeled as a log-normal distribution, or with the skewness parameter, as ranging from a log-normal to symmetric normal distribution. The MDER is estimated as a weighted average of dietary energy requirements for each sex-age group, and the PoU is calculated as the percentage of the modeled dietary energy consumption distribution that falls below this MDER.

Cross-country comparability using this data is limited due to the previously stated data concerns in the first model parameter (the previous food supply variable) and because the second and third parameters are derived from household surveys that may have differing quality of data collection. Still, the FAO deems cross-country and temporal comparability to be high since the same method is used to compute the PoU in each region. In any case, as with the previous outcome, I bypass cross-country comparisons and only estimate within-country effects in all regression analyses using the PoU variable. The FAO also cautions that the precision of PoU estimates is low, with margins of error likely exceeding 2.5pp, due to the uncertainty associated with each of the estimated parameters in the model. This noise is captured in the residual error term in my regression specifications but hinders the statistical power of the analyses.

Appendix C Additional Tables

Table 9: Country and Region Assignment into ENSO-Teleconnected and Weakly Affected Groups

	ENSO-teleconnected	Weakly affected
Countries	Angola; Antigua and Barbuda; Aruba; Australia; Bahamas; Bangladesh; Barbados; Belize; Benin; Bolivia (Plurinational State of); Botswana; Brazil; Brunei Darussalam; Burkina Faso; Burundi; Cabo Verde; Cambodia; Cameroon; Central African Republic; Chad; China, Hong Kong SAR; China, Macao SAR; China, Taiwan Province of; Colombia; Comoros; Congo; Costa Rica; Cote d'Ivoire; Cuba; Djibouti; Dominica; Dominican Republic; Ecuador; El Salvador; Equatorial Guinea; Eswatini; Ethiopia; Gabon; Gambia; Ghana; Grenada; Guatemala; Guinea; Guinea-Bissau; Guyana; Haiti; Honduras; India; Indonesia; Jamaica; Kenya; Lao People's Democratic Republic; Lesotho; Liberia; Madagascar; Malawi; Malaysia; Maldives; Mali; Mauritania; Mauritius; Mexico; Morocco; Mozambique; Myanmar; Namibia; Nicaragua; Niger; Nigeria; Oman; Panama; Paraguay; Peru; Philippines; Rwanda; Saint Kitts and Nevis; Saint Lucia; Saint Vincent and the Grenadines; Sao Tome and Principe; Senegal; Seychelles; Sierra Leone; Singapore; South Africa; South Sudan; Sri Lanka; Suriname; Thailand; Timor-Leste; Togo; Trinidad and Tobago; Uganda; United Arab Emirates; United Republic of Tanzania; Venezuela (Bolivarian Republic of); Viet Nam; Yemen; Zambia; Zimbabwe	Afghanistan; Aland Islands; Albania; Algeria; Andorra; Argentina; Armenia; Austria; Azerbaijan; Bahrain; Belarus; Belgium; Bhutan; Bosnia and Herzegovina; Bulgaria; Canada; Chile; China, mainland; Croatia; Cyprus; Czechia; Democratic People's Republic of Korea; Denmark; Egypt; Estonia; Fiji; Finland; France; Georgia; Germany; Greece; Hungary; Iceland; Iran (Islamic Republic of); Iraq; Ireland; Israel; Italy; Japan; Jordan; Kazakhstan; Kiribati; Kuwait; Kyrgyzstan; Latvia; Lebanon; Lithuania; Luxembourg; Malta; Mongolia; Montenegro; Nepal; Netherlands; New Zealand; North Macedonia; Norway; Pakistan; Poland; Portugal; Qatar; Republic of Korea; Republic of Moldova; Romania; Russian Federation; San Marino; Saudi Arabia; Serbia; Slovakia; Slovenia; Solomon Islands; Spain; Sweden; Switzerland; Tajikistan; Tunisia; Turkey; Turkmenistan; Ukraine; United Kingdom; United States of America; Uruguay; Uzbekistan; Vanuatu
Regions	Australia and New Zealand; Caribbean; Central America; Eastern Africa; Middle Africa; South America; South-Eastern Asia; Southern Africa; Southern Asia; Western Africa	Central Asia; Eastern Asia; Eastern Europe; Northern Africa; Northern America; Northern Europe; Southern Europe; Western Asia; Western Europe

Notes: ENSO-teleconnection assignment of all countries and regions in at least one study sample. See Hsiang, Meng, and Cane (2011) for details on the methodology of country assignment. Regions are assigned ENSO-teleconnected or weakly affected based on the population-weighted mode of the countries that make up the region.

Table 10: Dummy Regressions of Food Supply Per Capita Per Day on NINO3.4 By Country Group

	ENSO-teleconnected	Weakly affected
	(1)	(2)
	FS/c/d	FS/c/d
$\text{NINO3.4}_t \in [-1.5, -0.75)$	2.232	-3.022
	(9.197)	(11.00)
$\text{NINO3.4}_t \in [-0.75, -0.25)$	-2.728	11.32
	(9.396)	(11.92)
$\text{NINO3.4}_t \in [-0.25, 0.25)$	0	0
$\text{NINO3.4}_t \in [0.25, 0.75)$	-10.76	15.46
	(9.205)	(10.48)
$\text{NINO3.4}_t \in [0.75, 1.25)$	-13.81	-15.48
	(12.48)	(14.29)
$\text{NINO3.4}_t \in [1.25, 2.0]$	-7.769	22.26
	(12.12)	(16.31)
$\text{NINO3.4}_{t-1} \in [-1.5, -0.75)$	-5.865	3.363
	(9.786)	(13.17)
$\text{NINO3.4}_{t-1} \in [-0.75, -0.25)$	-6.245	16.32
	(9.086)	(11.30)
$\text{NINO3.4}_{t-1} \in [-0.25, 0.25)$	0	0
$\text{NINO3.4}_{t-1} \in [0.25, 0.75)$	-2.740	20.02*
	(8.816)	(10.24)
$\text{NINO3.4}_{t-1} \in [0.75, 1.25)$	-11.24	-2.109
	(12.61)	(14.26)
$\text{NINO3.4}_{t-1} \in [1.25, 2.0]$	-15.43	35.51**
	(12.80)	(17.77)
Country fixed effects	Yes	Yes
Country-specific linear trends	Yes	Yes
Observations	4815	3260
Adjusted R^2	0.997	0.998
Mean of dependent variable	2,311	2,930

Notes: The dependent variable is food supply per capita per day (kcal). Each observation is a country-year, and the sample period is 1961-2013. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Each variable is a dummy for NINO3.4 being in the given interval; coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. Standard errors in parentheses are adjusted for spatial correlation (2,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Preferred Regressions of Food Supply Per Capita Per Day on NINO3.4 By Country Group With Varying Standard Errors

	ENSO-teleconnected			Weakly affected		
	(1) FS/c/d	(2) FS/c/d	(3) FS/c/d	(4) FS/c/d	(5) FS/c/d	(6) FS/c/d
$NINO3.4_t$ (°C)	-3.368	-3.368	-3.368	2.195	2.195	2.195
	(3.578)	(3.625)	(4.119)	(4.395)	(4.487)	(5.019)
$NINO3.4_{t-1}$ (°C)	-2.362	-2.362	-2.362	3.035	3.035	3.035
	(3.458)	(3.497)	(3.936)	(4.669)	(4.777)	(5.357)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific linear trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4815	4815	4815	3260	3260	3260
Adjusted R^2	0.997	0.997	0.997	0.998	0.998	0.998
Mean of dependent variable	2,311	2,311	2,311	2,930	2,930	2,930
Spatial correlation (km)	2000	2000	4000	2000	2000	4000
Serial correlation (years)	5	10	5	5	10	5

Notes: The dependent variable is food supply per capita per day (kcal). Each observation is a country-year, and the sample period is 1961-2013. $NINO3.4_t$ is the monthly NINO3.4 series averaged over May-December of year t. Standard errors in parentheses are adjusted for spatial correlation and serial correlation over varying distances and time lags. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Preferred Regressions of Food Consumer Price Index on NINO3.4 By Country Group With Varying Standard Errors

	ENSO-teleconnected			Weakly affected		
	(1) FCPI	(2) FCPI	(3) FCPI	(4) FCPI	(5) FCPI	(6) FCPI
$\text{NINO3.4}_t \in [-1.5, -0.75)$	-2.220***	-2.220***	-2.220***	-0.0390	-0.0390	-0.0390
	(0.604)	(0.713)	(0.760)	(0.705)	(0.744)	(0.703)
$\text{NINO3.4}_t \in [-0.75, -0.25)$	1.567***	1.567**	1.567**	2.191***	2.191***	2.191***
	(0.595)	(0.651)	(0.798)	(0.728)	(0.741)	(0.755)
$\text{NINO3.4}_t \in [-0.25, 0.25)$	0	0	0	0	0	0
$\text{NINO3.4}_t \in [0.25, 0.75)$	2.290***	2.290***	2.290***	2.809***	2.809***	2.809***
	(0.424)	(0.481)	(0.550)	(0.684)	(0.687)	(0.789)
$\text{NINO3.4}_t \in [0.75, 1.25)$	0.226	0.226	0.226	1.393**	1.393**	1.393**
	(0.602)	(0.611)	(0.809)	(0.579)	(0.570)	(0.651)
$\text{NINO3.4}_t \in [1.25, 2.0]$	-0.546	-0.546	-0.546	-0.534	-0.534	-0.534
	(0.985)	(0.996)	(1.248)	(1.115)	(1.132)	(1.208)
$\text{NINO3.4}_{t-1} \in [-1.5, -0.75)$	-3.153***	-3.153***	-3.153***	-1.159*	-1.159*	-1.159*
	(0.644)	(0.570)	(0.876)	(0.619)	(0.612)	(0.673)
$\text{NINO3.4}_{t-1} \in [-0.75, -0.25)$	0.116	0.116	0.116	0.940**	0.940**	0.940**
	(0.521)	(0.545)	(0.680)	(0.445)	(0.452)	(0.474)
$\text{NINO3.4}_{t-1} \in [-0.25, 0.25)$	0	0	0	0	0	0
$\text{NINO3.4}_{t-1} \in [0.25, 0.75)$	1.944***	1.944***	1.944**	2.997***	2.997***	2.997***
	(0.623)	(0.626)	(0.873)	(0.507)	(0.501)	(0.511)
$\text{NINO3.4}_{t-1} \in [0.75, 1.25)$	2.237***	2.237***	2.237***	2.323***	2.323***	2.323***
	(0.679)	(0.685)	(0.848)	(0.610)	(0.604)	(0.606)
$\text{NINO3.4}_{t-1} \in [1.25, 2.0]$	0.778	0.778	0.778	1.086**	1.086**	1.086**
	(0.570)	(0.605)	(0.662)	(0.468)	(0.471)	(0.472)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific linear trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1060	1060	1060	1066	1066	1066
Adjusted R^2	0.998	0.998	0.998	0.999	0.999	0.999
Mean of dependent variable	100.749	100.749	100.749	99.445	99.445	99.445
Spatial correlation (km)	2000	2000	4000	2000	2000	4000
Serial correlation (years)	5	10	5	5	10	5

Notes: The dependent variable is Food Consumer Price Index (2010 = 100). Each observation is a country-tropical-year, and the sample period is tropical years 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over tropical year t. Each variable is a dummy for NINO3.4 being in the given interval; coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. Standard errors in parentheses are adjusted for spatial correlation and serial correlation over varying distances and time lags. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Preferred Regressions of Prevalence of Undernourishment on NINO3.4 in ENSO-Teleconnected Regions With Varying Standard Errors

	ENSO-teleconnected		
	(1) PoU	(2) PoU	(3) PoU
$\text{NINO3.4}_t \in [-1.5, -0.75)$	-0.623***	-0.623**	-0.623***
	(0.236)	(0.247)	(0.205)
$\text{NINO3.4}_t \in [-0.75, -0.25)$	0.282	0.282	0.282
	(0.344)	(0.380)	(0.275)
$\text{NINO3.4}_t \in [-0.25, 0.25)$	0	0	0
$\text{NINO3.4}_t \in [0.25, 0.75)$	0.258	0.258	0.258
	(0.447)	(0.461)	(0.427)
$\text{NINO3.4}_t \in [0.75, 1.25)$	-0.177	-0.177	-0.177
	(0.484)	(0.484)	(0.536)
$\text{NINO3.4}_t \in [1.25, 2.0]$	0.0168	0.0168	0.0168
	(0.367)	(0.379)	(0.248)
$\text{NINO3.4}_{t-1} \in [-1.5, -0.75)$	-0.235	-0.235	-0.235
	(0.425)	(0.406)	(0.416)
$\text{NINO3.4}_{t-1} \in [-0.75, -0.25)$	0.552*	0.552	0.552
	(0.324)	(0.344)	(0.340)
$\text{NINO3.4}_{t-1} \in [-0.25, 0.25)$	0	0	0
$\text{NINO3.4}_{t-1} \in [0.25, 0.75)$	0.236	0.236	0.236
	(0.472)	(0.483)	(0.434)
$\text{NINO3.4}_{t-1} \in [0.75, 1.25)$	0.352	0.352	0.352
	(0.466)	(0.462)	(0.478)
$\text{NINO3.4}_{t-1} \in [1.25, 2.0]$	0.652	0.652	0.652
	(0.491)	(0.471)	(0.464)
Region fixed effects	Yes	Yes	Yes
Region-specific linear trends	Yes	Yes	Yes
Observations	190	190	190
Adjusted R^2	0.997	0.997	0.997
Mean of dependent variable	15.198	15.198	15.198
Spatial correlation (km)	4000	4000	8000
Serial correlation (years)	5	10	5

Notes: The dependent variable is prevalence of undernourishment (%). Each observation is a region-year, and the sample period is 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Each variable is a dummy for NINO3.4 being in the given interval; coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. Standard errors in parentheses are adjusted for spatial correlation and serial correlation over varying distances and time lags. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: Preferred Regressions of Prevalence of Undernourishment on NINO3.4 in Weakly Affected Regions With Varying Standard Errors

	Weakly affected		
	(1) PoU	(2) PoU	(3) PoU
NINO3.4_t (°C)	0.131*	0.131*	0.131*
	(0.0723)	(0.0727)	(0.0766)
NINO3.4_{t-1} (°C)	0.0561	0.0561	0.0561
	(0.0683)	(0.0713)	(0.0684)
Region fixed effects	Yes	Yes	Yes
Region-specific linear trends	Yes	Yes	Yes
Observations	171	171	171
Adjusted R^2	0.991	0.991	0.991
Mean of dependent variable	4.828	4.828	4.828
Spatial correlation (km)	4000	4000	8000
Serial correlation (years)	5	10	5

Notes: The dependent variable is prevalence of undernourishment (%). Each observation is a region-year, and the sample period is 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Standard errors in parentheses are adjusted for spatial correlation and serial correlation over varying distances and time lags. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 15: Preferred Regressions of Food Supply Per Capita Per Day on NINO3.4 By Country Group With Varying Country Trends

	ENSO-teleconnected			Weakly affected		
	(1) FS/c/d	(2) FS/c/d	(3) FS/c/d	(4) FS/c/d	(5) FS/c/d	(6) FS/c/d
NINO3.4_t (°C)	-3.836	-3.368	-2.686	-0.395	2.195	-0.0628
	(5.506)	(3.578)	(2.872)	(6.772)	(4.395)	(3.247)
NINO3.4_{t-1} (°C)	-2.791	-2.362	-1.710	-0.425	3.035	0.914
	(5.387)	(3.458)	(2.793)	(6.882)	(4.669)	(3.517)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Linear trend	Yes	No	No	Yes	No	No
Country-specific linear trends	No	Yes	Yes	No	Yes	Yes
Country-specific quadratic trends	No	No	Yes	No	No	Yes
Observations	4815	4815	4815	3260	3260	3260
Adjusted R^2	0.994	0.997	0.998	0.995	0.998	0.999
Mean of dependent variable	2,311	2,311	2,311	2,930	2,930	2,930

Notes: The dependent variable is food supply per capita per day (kcal). Each observation is a country-year, and the sample period is 1961-2013. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Standard errors in parentheses are adjusted for spatial correlation (2,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 16: Preferred Regressions of Food Consumer Price Index on NINO3.4 By Country Group With Varying Country Trends

	ENSO-teleconnected			Weakly affected		
	(1) FCPI	(2) FCPI	(3) FCPI	(4) FCPI	(5) FCPI	(6) FCPI
$\text{NINO3.4}_t \in [-1.5, -0.75)$	-3.841**	-2.220***	-2.262***	-0.373	-0.0390	0.0619
	(1.769)	(0.604)	(0.547)	(1.381)	(0.705)	(0.528)
$\text{NINO3.4}_t \in [-0.75, -0.25)$	0.528	1.567***	0.298	1.953*	2.191***	2.191***
	(1.353)	(0.595)	(0.568)	(1.179)	(0.728)	(0.525)
$\text{NINO3.4}_t \in [-0.25, 0.25)$	0	0	0	0	0	0
$\text{NINO3.4}_t \in [0.25, 0.75)$	2.091***	2.290***	2.092***	2.537**	2.809***	2.642***
	(0.784)	(0.424)	(0.483)	(1.011)	(0.684)	(0.535)
$\text{NINO3.4}_t \in [0.75, 1.25)$	0.305	0.226	0.515	1.162	1.393**	1.160**
	(1.160)	(0.602)	(0.527)	(1.014)	(0.579)	(0.460)
$\text{NINO3.4}_t \in [1.25, 2.0]$	-2.093	-0.546	-2.576**	-0.370	-0.534	-0.112
	(2.248)	(0.985)	(1.013)	(2.016)	(1.115)	(0.839)
$\text{NINO3.4}_{t-1} \in [-1.5, -0.75)$	-3.162***	-3.153***	-2.006***	-1.168	-1.159*	-1.170**
	(0.817)	(0.644)	(0.475)	(0.906)	(0.619)	(0.513)
$\text{NINO3.4}_{t-1} \in [-0.75, -0.25)$	-0.980	0.116	-0.650	0.854	0.940**	1.016***
	(1.140)	(0.521)	(0.487)	(0.872)	(0.445)	(0.374)
$\text{NINO3.4}_{t-1} \in [-0.25, 0.25)$	0	0	0	0	0	0
$\text{NINO3.4}_{t-1} \in [0.25, 0.75)$	2.210*	1.944***	2.666***	2.684**	2.997***	2.582***
	(1.295)	(0.623)	(0.547)	(1.123)	(0.507)	(0.452)
$\text{NINO3.4}_{t-1} \in [0.75, 1.25)$	2.738	2.237***	2.186***	2.444*	2.323***	2.127***
	(1.680)	(0.679)	(0.547)	(1.320)	(0.610)	(0.503)
$\text{NINO3.4}_{t-1} \in [1.25, 2.0]$	0.109	0.778	-0.229	1.180	1.086**	1.053***
	(1.242)	(0.570)	(0.461)	(0.884)	(0.468)	(0.358)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Linear trend	Yes	No	No	Yes	No	No
Country-specific linear trends	No	Yes	Yes	No	Yes	Yes
Country-specific quadratic trends	No	No	Yes	No	No	Yes
Observations	1060	1060	1060	1066	1066	1066
Adjusted R^2	0.993	0.998	0.999	0.997	0.999	0.999
Mean of dependent variable	100.749	100.749	100.749	99.445	99.445	99.445

Notes: The dependent variable is Food Consumer Price Index (2010 = 100). Each observation is a country-tropical-year, and the sample period is tropical years 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over tropical year t. Each variable is a dummy for NINO3.4 being in the given interval; coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. Standard errors in parentheses are adjusted for spatial correlation (2,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 17: Preferred Regressions of Prevalence of Undernourishment on NINO3.4 in ENSO-Teleconnected Regions With Varying Region Trends

	ENSO-teleconnected		
	(1) PoU	(2) PoU	(3) PoU
$\text{NINO3.4}_t \in [-1.5, -0.75)$	-0.623*	-0.623***	-0.397***
	(0.352)	(0.236)	(0.117)
$\text{NINO3.4}_t \in [-0.75, -0.25)$	0.282	0.282	-0.0972
	(0.497)	(0.344)	(0.140)
$\text{NINO3.4}_t \in [-0.25, 0.25)$	0	0	0
$\text{NINO3.4}_t \in [0.25, 0.75)$	0.258	0.258	0.157
	(0.574)	(0.447)	(0.179)
$\text{NINO3.4}_t \in [0.75, 1.25)$	-0.177	-0.177	0.188
	(0.593)	(0.484)	(0.134)
$\text{NINO3.4}_t \in [1.25, 2.0]$	0.0168	0.0168	-0.866***
	(0.715)	(0.367)	(0.222)
$\text{NINO3.4}_{t-1} \in [-1.5, -0.75)$	-0.235	-0.235	-0.205
	(0.526)	(0.425)	(0.175)
$\text{NINO3.4}_{t-1} \in [-0.75, -0.25)$	0.552	0.552*	-0.205*
	(0.510)	(0.324)	(0.123)
$\text{NINO3.4}_{t-1} \in [-0.25, 0.25)$	0	0	0
$\text{NINO3.4}_{t-1} \in [0.25, 0.75)$	0.236	0.236	0.405*
	(0.609)	(0.472)	(0.225)
$\text{NINO3.4}_{t-1} \in [0.75, 1.25)$	0.352	0.352	0.310
	(0.618)	(0.466)	(0.209)
$\text{NINO3.4}_{t-1} \in [1.25, 2.0]$	0.652	0.652	-0.0149
	(0.674)	(0.491)	(0.233)
Region fixed effects	Yes	Yes	Yes
Linear trend	Yes	No	No
Region-specific linear trends	No	Yes	Yes
Region-specific quadratic trends	No	No	Yes
Observations	190	190	190
Adjusted R^2	0.988	0.997	0.999
Mean of dependent variable	15.198	15.198	15.198

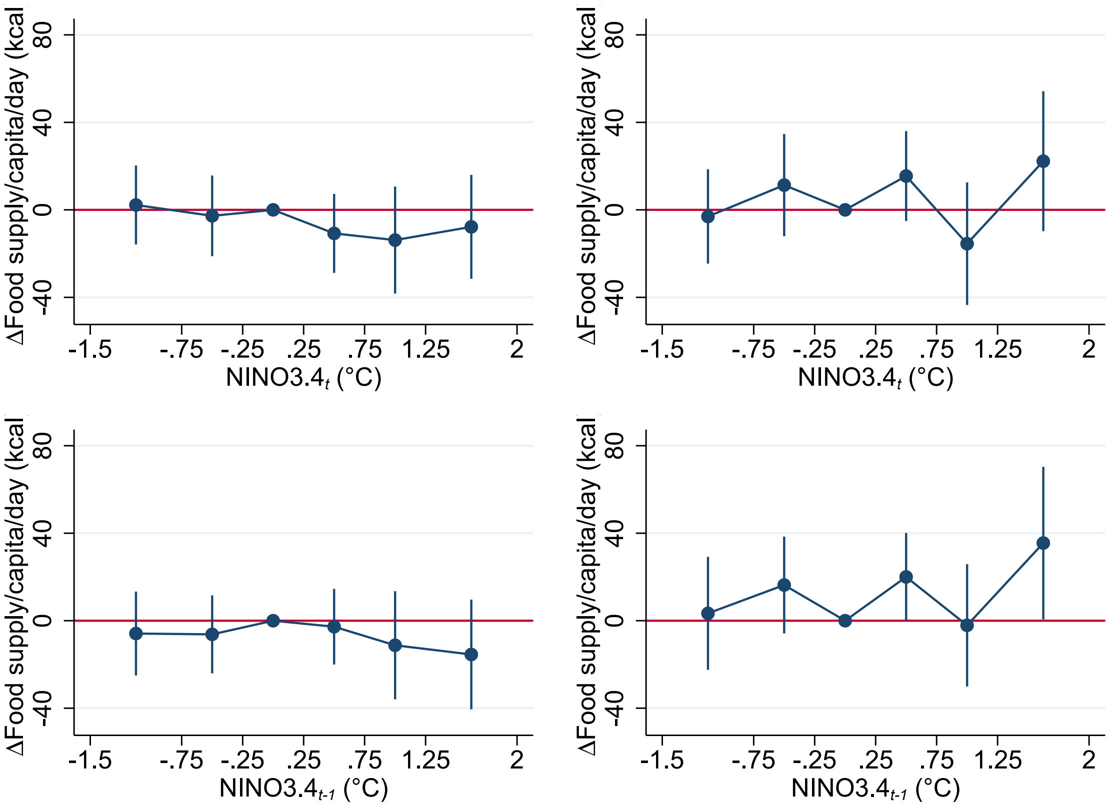
Notes: The dependent variable is prevalence of undernourishment (%). Each observation is a region-year, and the sample period is 2000-2018. NINO3.4_t is the monthly NINO3.4 series averaged over May-December of year t. Each variable is a dummy for NINO3.4 being in the given interval; coefficients estimate effects relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. Standard errors in parentheses are adjusted for spatial correlation (4,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 18: Preferred Regressions of Prevalence of Undernourishment on NINO3.4 in Weakly Affected Regions With Varying Region Trends

	Weakly affected		
	(1) PoU	(2) PoU	(3) PoU
NINO3.4$_t$ (°C)	0.131	0.131*	0.0786**
	(0.194)	(0.0723)	(0.0376)
NINO3.4$_{t-1}$ (°C)	0.0561	0.0561	0.0714**
	(0.209)	(0.0683)	(0.0339)
Region fixed effects	Yes	Yes	Yes
Linear trend	Yes	No	No
Region-specific linear trends	No	Yes	Yes
Region-specific quadratic trends	No	No	Yes
Observations	171	171	171
Adjusted R^2	0.955	0.991	0.995
Mean of dependent variable	4.828	4.828	4.828

Notes: The dependent variable is prevalence of undernourishment (%). Each observation is a region-year, and the sample period is 2000-2018. NINO3.4$_t$ is the monthly NINO3.4 series averaged over May-December of year t. Standard errors in parentheses are adjusted for spatial correlation (4,000 km) and serial correlation (5 years). Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix D Additional Figures



(a) ENSO-Teleconnected

(b) Weakly Affected

Figure 12: Estimated Effects of NINO3.4 on Food Supply Per Capita Per Day By Country Group and Period. *Notes:* Coefficients from dummy regressions of food supply per capita per day on NINO3.4 (Table 10) are plotted separately by country group and period. Coefficients estimate effects of NINO3.4 being in the given interval relative to NINO3.4 being in the neutral interval $[-0.25, 0.25)$. 95% confidence intervals are shown using standard errors adjusted for spatial correlation (2,000 km) and serial correlation (5 years).

References

Adams, Richard M., Chi-Chung Chen, Bruce A. McCarl, and Rodney F. Weiher. 1999. "The economic consequences of ENSO events for agriculture." *Climate Research* 13, no. 3 (December 10): 165–172. doi:`10.3354/cr013165`.

Alem, Yonas, and Måns Söderbom. 2012. "Household-Level Consumption in Urban Ethiopia: The Effects of a Large Food Price Shock." *World Development* 40, no. 1 (January 1): 146–162. doi:`10.1016/j.worlddev.2011.04.020`.

Bacon, Christopher M., William A. Sundstrom, Iris T. Stewart, and David Beezer. 2017. "Vulnerability to Cumulative Hazards: Coping with the Coffee Leaf Rust Outbreak, Drought, and Food Insecurity in Nicaragua." *World Development* 93 (May 1): 136–152. doi:`10.1016/j.worlddev.2016.12.025`.

Barnard, Patrick L., Andrew D. Short, Mitchell D. Harley, Kristen D. Splinter, Sean Vitousek, Ian L. Turner, Jonathan Allan, et al. 2015. "Coastal vulnerability across the Pacific dominated by El Niño/Southern Oscillation." *Nature Geoscience* 8, no. 10 (October): 801–807. doi:10.1038/ngeo2539.

Berry, Brian J. L., and Adam Okulicz-Kozaryn. 2008. "Are there ENSO signals in the macroeconomy?" *Ecological Economics* 64, no. 3 (January 15): 625–633. doi:10.1016/j.ecolecon.2007.04.009.

Brunner, Allan D. 2002. "El Niño and World Primary Commodity Prices: Warm Water or Hot Air?" *The Review of Economics and Statistics* 84, no. 1 (February 1): 176–183. doi:10.1162/003465302317332008.

Camargo, Suzana J., and Adam H. Sobel. 2005. "Western North Pacific Tropical Cyclone Intensity and ENSO." *Journal of Climate* 18, no. 15 (August 1): 2996–3006. doi:10.1175/JCLI3457.1.

Cane, Mark A., Gidon Eshel, and R. W. Buckland. 1994. "Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature." *Nature* 370, no. 6486 (July): 204–205. doi:10.1038/370204a0.

Cashin, Paul, Kamiar Mohaddes, and Mehdi Raissi. 2017. "Fair weather or foul? The macroeconomic effects of El Niño." *Journal of International Economics* 106 (May): 37–54. doi:10.1016/j.jinteco.2017.01.010.

Changnon, Stanley A. 1999. "Impacts of 1997–98 EI Niño–Generated Weather in the United States." *Bulletin of the American Meteorological Society* 80, no. 9 (September 1): 1819–1828. doi:10.1175/1520-0477(1999)080<1819:IOENOG>2.0.CO;2.

Chen, Dake, and Mark A. Cane. 2008. "El Niño prediction and predictability." *Journal of Computational Physics,* Predicting weather, climate and extreme events, 227, no. 7 (March 20): 3625–3640. doi:10.1016/j.jcp.2007.05.014.

Chen, Dake, Mark A. Cane, Alexey Kaplan, Stephen E. Zebiak, and Daji Huang. 2004. "Predictability of El Niño over the past 148 years." *Nature* 428, no. 6984 (April): 733–736. doi:10.1038/nature02439.

Chiang, John C. H., and Adam H. Sobel. 2002. "Tropical Tropospheric Temperature Variations Caused by ENSO and Their Influence on the Remote Tropical Climate." *Journal of Climate* 15, no. 18 (September 1): 2616–2631. doi:10.1175/1520-0442(2002)015<2616:TTTVCB>2.0.CO;2.

Clarke, Allan J. 2014. "El Niño Physics and El Niño Predictability." *Annual Review of Marine Science* 6 (1): 79–99. doi:10.1146/annurev-marine-010213-135026.

Climate Prediction Center Internet Team. 2009. "Climate Prediction Center - Monitoring & Data: Oceanic & Atmospheric Climate Data." Oceanic & Atmospheric Climate Data. August 4. Accessed January 28, 2020. https://www.cpc.ncep.noaa.gov/products/monitoring_and_data/oadata.shtml.

Cobb, Kim M., Niko Westphal, Hussein R. Sayani, Jordan T. Watson, Emanuele Di Lorenzo, H. Cheng, R. L. Edwards, and Christopher D. Charles. 2013. "Highly Variable El Niño–Southern Oscillation Throughout the Holocene." *Science* 339, no. 6115 (January 4): 67–70. doi:10.1126/science.1228246.

Conley, T. G. 1999. "GMM estimation with cross sectional dependence." *Journal of Econometrics* 92, no. 1 (September 1): 1–45. doi:10.1016/S0304-4076(98)00084-0.

Demeke, Abera Birhanu, Alwin Keil, and Manfred Zeller. 2011. "Using panel data to estimate the effect of rainfall shocks on smallholders food security and vulnerability in rural Ethiopia." *Climatic Change* 108, no. 1 (September): 185–206. doi:10.1007/s10584-010-9994-3.

Deng, Xiangzheng, Jikun Huang, Fangbin Qiao, Rosamond L. Naylor, Walter P. Falcon, Marshall Burke, Scott Rozelle, and David Battisti. 2010. "Impacts of El Nino-Southern Oscillation events on China's rice production." *Journal of Geographical Sciences* 20, no. 1 (February 1): 3–16. doi:10.1007/s11442-010-0003-6.

Dharmasena, Senarath, David A. Bessler, and Oral Capps. 2016. "Food environment in the United States as a complex economic system." *Food Policy* 61 (May 1): 163–175. doi:10.1016/j.foodpol.2016.03.003.

Donnelly, Jeffrey P., and Jonathan D. Woodruff. 2007. "Intense hurricane activity over the past 5,000 years controlled by El Niño and the West African monsoon." *Nature* 447, no. 7143 (May): 465–468. doi:10.1038/nature05834.

Etzold, Benjamin, Ahsan Uddin Ahmed, Selim Reza Hassan, and Sharmind Neelormi. 2014. "Clouds gather in the sky, but no rain falls. Vulnerability to rainfall variability and food insecurity in Northern Bangladesh and its effects on migration." *Climate and Development* 6, no. 1 (January 2): 18–27. doi:10.1080/17565529.2013.833078.

Falcon, Walter P., Rosamond L. Naylor, Whitney L. Smith, Marshall B. Burke, and Ellen B. McCullough. 2004. "Using climate models to improve Indonesian food security." *Bulletin of Indonesian Economic Studies* 40, no. 3 (December 1): 355–377. doi:10.1080/0007491042000231520.

FAO. 2019. "FAOSTAT." Data. Accessed January 16, 2020. http://www.fao.org/faostat/en/#data.

FAO, IFAD, UNICEF, WFP and WHO. 2019. *The State of Food Security and Nutrition in the World 2019. Safeguarding against economic slowdowns and downturns.* Rome: FAO.

Fink, Günther, Evan Peet, Goodarz Danaei, Kathryn Andrews, Dana Charles McCoy, Christopher R Sudfeld, Mary C Smith Fawzi, Majid Ezzati, and Wafaie W Fawzi. 2016. "Schooling and wage income losses due to early-childhood growth faltering in developing countries: national, regional, and global estimates." *The American Journal of Clinical Nutrition* 104, no. 1 (July 1): 104–112. doi:10.3945/ajcn.115.123968.

Grace, Kathryn, Molly Brown, and Amy McNally. 2014. "Examining the link between food prices and food insecurity: A multi-level analysis of maize price and birthweight in Kenya." *Food Policy* 46 (June 1): 56–65. doi:10.1016/j.foodpol.2014.01.010.

Gregory, Christian A., and Alisha Coleman-Jensen. 2013. "Do High Food Prices Increase Food Insecurity in the United States?" *Applied Economic Perspectives and Policy* 35, no. 4 (December 1): 679–707. doi:10.1093/aepp/ppt024.

Gundersen, Craig, and James P. Ziliak. 2015. "Food Insecurity And Health Outcomes." *Health Affairs* 34, no. 11 (November 1): 1830–1839. doi:10.1377/hlthaff.2015.0645.

———. 2018. "Food Insecurity Research in the United States: Where We Have Been and Where We Need to Go." *Applied Economic Perspectives and Policy* 40, no. 1 (March 1): 119–135. doi:10.1093/aepp/ppx058.

Hales, Simon, Sally Edwards, and Sari Kovats. 2003. "Impacts on health of climate extremes." In *Climate Change and Human Health,* 79–102.

Halpert, Michael S., and Chester F. Ropelewski. 1992. "Surface Temperature Patterns Associated with the Southern Oscillation." *Journal of Climate* 5, no. 6 (June 1): 577–593. doi:10.1175/1520-0442(1992)005<0577:STPAWT>2.0.CO;2.

Hamelin, Anne-Marie, Micheline Beaudry, and Jean-Pierre Habicht. 2002. "Characterization of household food insecurity in Québec: food and feelings." *Social Science & Medicine* 54, no. 1 (January 1): 119–132. doi:10.1016/S0277-9536(01)00013-2.

Hansen, J. W., J. W. Jones, A. Irmak, and F. Royce. 2015. "El Niño-Southern Oscillation Impacts on Crop Production in the Southeast United States." In *Impacts of El Niño and Climate Variability on Agriculture,* 55–76. John Wiley & Sons, Ltd. doi:10.2134/asaspecpub63.ch4.

Hoddinott, John, Harold Alderman, Jere R. Behrman, Lawrence Haddad, and Susan Horton. 2013. "The economic rationale for investing in stunting reduction: Economic rationale for stunting reduction." *Maternal & Child Nutrition* 9 (September): 69–82. doi:10.1111/mcn.12080.

Horton, Sue, and Richard H Steckel. 2011. "Malnutrition Global economic losses attributable to malnutrition 1900- 2000 and projections to 2050." *Assessment Paper: Copenhagen Consensus on Human Challenges:* 37.

Hsiang, Solomon, and Robert E. Kopp. 2018. "An Economist's Guide to Climate Change Science." *Journal of Economic Perspectives* 32, no. 4 (November): 3–32. doi:10.1257/jep.32.4.3.

Hsiang, Solomon M. 2010. "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America." *Proceedings of the National Academy of Sciences* 107, no. 35 (August 31): 15367–15372. doi:10.1073/pnas.1009510107.

Hsiang, Solomon M., and Kyle C. Meng. 2015. "Tropical Economics." *American Economic Review* 105, no. 5 (May): 257–261. doi:10.1257/aer.p20151030.

Hsiang, Solomon M., Kyle C. Meng, and Mark A. Cane. 2011. "Civil conflicts are associated with the global climate." *Nature* 476, no. 7361 (August): 438–441. doi:10.1038/nature10311.

Iizumi, Toshichika, Jing-Jia Luo, Andrew J. Challinor, Gen Sakurai, Masayuki Yokozawa, Hirofumi Sakuma, Molly E. Brown, and Toshio Yamagata. 2014. "Impacts of El Niño Southern Oscillation on the global yields of major crops." *Nature Communications* 5, no. 1 (September). doi:10.1038/ncomms4712.

Kendall, ANNE, CHRISTINE M. Olson, and EDWARD A. Frongillo. 1996. "Relationship of Hunger and Food Insecurity to Food Availability and Consumption." *Journal of the American Dietetic Association* 96, no. 10 (October 1): 1019–1024. doi:10.1016/S0002-8223(96)00271-4.

Kidane, H., Z. G. Alemu, and G. Kundhlande. 2005. "Causes of Household Food Insecurity in Koredegaga Peasant Association, Oromiya Zone, Ethiopia." *Agrekon* 44, no. 4 (December 1): 543–560. doi:10.1080/03031853.2005.9523727.

Kovats, R Sari, Menno J Bouma, Shakoor Hajat, Eve Worrall, and Andy Haines. 2003. "El Niño and health." *The Lancet* 362, no. 9394 (November 1): 1481–1489. doi:10.1016/S0140-6736(03)14695-8.

Kushel, Margot B., Reena Gupta, Lauren Gee, and Jennifer S. Haas. 2006. "Housing instability and food insecurity as barriers to health care among low-income americans." *Jour-*

nal of General Internal Medicine 21, no. 1 (January 1): 71–77. doi:10.1111/j.1525-1497.2005.00278.x.

Lee, Jung Sun, Craig Gundersen, John Cook, Barbara Laraia, and Mary Ann Johnson. 2012. "Food Insecurity and Health across the Lifespan." *Advances in Nutrition* 3, no. 5 (September 1): 744–745. doi:10.3945/an.112.002543.

Lehnert, Thomas, Diana Sonntag, Alexander Konnopka, Steffi Riedel-Heller, and Hans-Helmut König. 2013. "Economic costs of overweight and obesity." *Best Practice & Research Clinical Endocrinology & Metabolism* 27, no. 2 (April): 105–115. doi:10.1016/j.beem.2013.01.002.

Loopstra, Rachel, Aaron Reeves, Martin McKee, and David Stuckler. 2016. "Food insecurity and social protection in Europe: Quasi-natural experiment of Europe's great recessions 2004-2012." *Preventive Medicine* 89 (August): 44–50. doi:10.1016/j.ypmed.2016.05.010.

Mechlem, Kerstin. 2004. "Food Security and the Right to Food in the Discourse of the United Nations." *European Law Journal* 10 (5): 631–648. doi:10.1111/j.1468-0386.2004.00235.x.

Messer, Ellen, and Marc J. Cohen. 2007. "Conflict, Food Insecurity and Globalization." *Food, Culture & Society* 10, no. 2 (July 1): 297–315. doi:10.2752/155280107X211458.

Misselhorn, Alison A. 2005. "What drives food insecurity in southern Africa? a meta-analysis of household economy studies." *Global Environmental Change* 15, no. 1 (April): 33–43. doi:10.1016/j.gloenvcha.2004.11.003.

Nord, Mark, and Linda S. Kantor. 2006. "Seasonal Variation in Food Insecurity Is Associated with Heating and Cooling Costs among Low-Income Elderly Americans." *The Journal of Nutrition* 136, no. 11 (November 1): 2939–2944. doi:10.1093/jn/136.11.2939.

Nyariki, D.M., S.L. Wiggins, and J.K. Imungi. 2002. "Levels and causes of household food and nutrition insecurity in dryland Kenya." *Ecology of Food and Nutrition* 41, no. 2 (March): 155–176. doi:10.1080/03670240214493.

Olson, Christine M. 1999. "Nutrition and Health Outcomes Associated with Food Insecurity and Hunger." *The Journal of Nutrition* 129, no. 2 (February 1): 521S–524S. doi:10.1093/jn/129.2.521S.

Patz, Jonathan A., Diarmid Campbell-Lendrum, Tracey Holloway, and Jonathan A. Foley. 2005. "Impact of regional climate change on human health." *Nature* 438, no. 7066 (November): 310–317. doi:10.1038/nature04188.

Pinstrup-Andersen, Per. 2009. "Food security: definition and measurement." *Food Security* 1, no. 1 (February): 5–7. doi:10.1007/s12571-008-0002-y.

Podestá, Guillermo P., Carlos D. Messina, Martín O. Grondona, and Graciela O. Magrin. 1999. "Associations between Grain Crop Yields in Central-Eastern Argentina and El Niño–Southern Oscillation." *Journal of Applied Meteorology* 38, no. 10 (October 1): 1488–1498. doi:10.1175/1520-0450(1999)038<1488:ABGCYI>2.0.CO;2.

Power, Scott, François Delage, Christine Chung, Greg Kociuba, and Kevin Keay. 2013. "Robust twenty-first-century projections of El Niño and related precipitation variability." *Nature* 502, no. 7472 (October): 541–545. doi:10.1038/nature12580.

Roberts, Martha G., David Dawe, Walter P. Falcon, and Rosamond L. Naylor. 2009. "El Niño–Southern Oscillation Impacts on Rice Production in Luzon, the Philippines." *Jour-*

nal of Applied Meteorology and Climatology 48, no. 8 (August 1): 1718–1724. doi:10.1175/2008JAMC1628.1.

Robinson, Jan, Patrice Guillotreau, Ramón Jiménez-Toribio, Frédéric Lantz, Lesya Nadzon, Juliette Dorizo, Calvin Gerry, and Francis Marsac. 2010. "Impacts of climate variability on the tuna economy of Seychelles." *Climate Research* 43, no. 3 (September 30): 149–162. doi:10.3354/cr00890.

Ropelewski, C. F., and M. S. Halpert. 1987. "Global and Regional Scale Precipitation Patterns Associated with the El Niño/Southern Oscillation." *Monthly Weather Review* 115, no. 8 (August 1): 1606–1626. doi:10.1175/1520-0493(1987)115<1606:GARSPP>2.0.CO;2.

Ropelewski, Chester F., and Michael S. Halpert. 1996. "Quantifying Southern Oscillation-Precipitation Relationships." *Journal of Climate* 9, no. 5 (May 1): 1043–1059. doi:10.1175/1520-0442(1996)009<1043:QSOPR>2.0.CO;2.

Rosa, William, ed. 2017. "Transforming Our World: The 2030 Agenda for Sustainable Development." In *A New Era in Global Health.* New York, NY: Springer Publishing Company, June. doi:10.1891/9780826190123.ap02.

Salafsky, Nick. 1994. "Drought in the rain forest: Effects of the 1991 El Niño-Southern Oscillation event on a rural economy in West Kalimantan, Indonesia." *Climatic Change* 27, no. 4 (August 1): 373–396. doi:10.1007/BF01096268.

Sarlio-Lähteenkorva, Sirpa, and Eero Lahelma. 2001. "Food Insecurity Is Associated with Past and Present Economic Disadvantage and Body Mass Index." *The Journal of Nutrition* 131, no. 11 (November 1): 2880–2884. doi:10.1093/jn/131.11.2880.

Schmidhuber, J., and F. N. Tubiello. 2007. "Global food security under climate change." *Proceedings of the National Academy of Sciences* 104, no. 50 (December 11): 19703–19708. doi:10.1073/pnas.0701976104.

Selvaraju, R. 2003. "Impact of El Niño–southern oscillation on Indian foodgrain production." *International Journal of Climatology* 23, no. 2 (February 1): 187–206. doi:10.1002/joc.869.

Smith, Lisa C., Amani E. El Obeid, and Helen H. Jensen. 2000. "The geography and causes of food insecurity in developing countries." *Agricultural Economics* 22 (2): 199–215. doi:10.1111/j.1574-0862.2000.tb00018.x.

Smith, Sarah C., and David Ubilava. 2017. "The El Niño Southern Oscillation and economic growth in the developing world." *Global Environmental Change* 45 (July 1): 151–164. doi:10.1016/j.gloenvcha.2017.05.007.

Tibesigwa, Byela, Martine Visser, Mark Collinson, and Wayne Twine. 2016. "Investigating the sensitivity of household food security to agriculture-related shocks and the implication of social and natural capital." *Sustainability Science* 11, no. 2 (March 1): 193–214. doi:10.1007/s11625-015-0332-6.

Timmermann, Axel, Soon-Il An, Jong-Seong Kug, Fei-Fei Jin, Wenju Cai, Antonietta Capotondi, Kim M. Cobb, et al. 2018. "El Niño–Southern Oscillation complexity." *Nature* 559, no. 7715 (July): 535–545. doi:10.1038/s41586-018-0252-6.

Tremmel, Maximilian, Ulf-G. Gerdtham, Peter Nilsson, and Sanjib Saha. 2017. "Economic Burden of Obesity: A Systematic Literature Review." *International Journal of Environmental Research and Public Health* 14, no. 4 (April 19): 435. doi:10.3390/ijerph14040435.

Trenberth, Kevin E., and Julie M. Caron. 2000. "The Southern Oscillation Revisited: Sea Level Pressures, Surface Temperatures, and Precipitation." *Journal of Climate* 13, no. 24 (December 1): 4358–4365. doi:10.1175/1520-0442(2000)013<4358:TSORSL>2.0.CO;2.

Tweeten, Luther. 1999. "The Economics of Global Food Security." *Applied Economic Perspectives and Policy* 21, no. 2 (October): 473–488. doi:10.2307/1349892.

U.S. Department of Health and Human Services and U.S. Department of Agriculture. 2015. *2015 – 2020 Dietary Guidelines for Americans.* 8th. December.

Ubilava, David. 2012. "El Niño, La Niña, and world coffee price dynamics." *Agricultural Economics* 43, no. 1 (January 1): 17–26. doi:10.1111/j.1574-0862.2011.00562.x.

United Nations. 1948. *The Universal Declaration of Human Rights.*

Verpoorten, Marijke, Abhimanyu Arora, Nik Stoop, and Johan Swinnen. 2013. "Self-reported food insecurity in Africa during the food price crisis." *Food Policy* 39 (January 30): 51–63. doi:10.1016/j.foodpol.2012.12.006.

Wang, Chunzai, Clara Deser, Jin-Yi Yu, Pedro DiNezio, and Amy Clement. 2017. "El Niño and Southern Oscillation (ENSO): A Review." In *Coral Reefs of the Eastern Tropical Pacific: Persistence and Loss in a Dynamic Environment,* edited by Peter W. Glynn, Derek P. Manzello, and Ian C. Enochs, 85–106. Coral Reefs of the World. Dordrecht: Springer Netherlands. doi:10.1007/978-94-017-7499-4_4.

Wolter, Klaus, and Michael S. Timlin. 2011. "El Niño/Southern Oscillation behaviour since 1871 as diagnosed in an extended multivariate ENSO index (MEI.ext)." *International Journal of Climatology* 31 (7): 1074–1087. doi:10.1002/joc.2336.

Ziervogel, Gina, Anthony Nyong, Balgis Osman, Cecilia Conde, Sergio Cortés, and Tom Downing. 2006. "Climate Variability and Change: Implications for Household Food Security." *AIACC Working Papers* (January).