



Discussion Paper

Deutsche Bundesbank
No 27/2025

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ISBN 978-3-98848-048-4

ISSN 2941-7503

From Weather to Wallet: Evidence on Seasonal Temperature Shocks and Global Food Prices*

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Abstract

In this paper, we provide evidence on the impact of *global* seasonal temperature shocks on *global* food commodity prices. Utilizing monthly data from 1961 to 2023, we find an economically and statistically highly significant, longer-lasting positive impact of summer temperature shocks on global food commodity prices. In contrast, we do not find such effects for winter, spring or autumn temperature shocks. A summer which is 0.4 °C hotter than in the previous five years, roughly equal to the largest summer shock we observe in our sample, causes food commodity prices to rise by about 10% within 12 months. In addition, we show that such weather shocks lower global food production quantities, indicating that such shocks can be classified as supply shocks.

KEYWORDS: Global seasonal temperature shocks, food commodity prices, food production, local projections.

JEL CLASSIFICATION: Q02, Q11, E31.

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1 Introduction

Global food commodity prices are highly volatile and have significant macroeconomic importance. Being able to forecast them and to understand the drivers behind this volatility is crucial, as changes in food prices can markedly impact economic activity and inflation dynamics (De Winne and Peersman, 2021; Peersman, 2022).¹

While geopolitical events, economic policies, and technological advancements have traditionally been cited as key factors influencing food prices (Headey and Fan, 2008; Piesse and Thirtle, 2009), recent research has increasingly focused on the role of local weather-related factors. For example, Roberts and Schlenker (2009) examine the impact of temperature anomalies on agricultural productivity in a panel of U. S. counties, showing that yields for specific food commodities, namely corn, soybeans and cotton, decline markedly at high temperatures. Similar evidence is documented by Tack, Barkley and Nalley (2015) and D’Agostino and Schlenker (2016) for grain yields in the U. S. as well as Lobell et al. (2011) for African maize trials and Welch et al. (2010) for rice yields in Asia. A direct link between temperature rises and commodity prices is presented by Letta, Montalbano and Pierre (2021) for crop prices in India. Also, Lobell, Schlenker and Costa-Roberts (2011) find a significant impact of climatic factors on grain yields and, by using estimated price elasticities², conclude that rising temperatures can increase average commodity prices considerably. Further studies based on global panel data suggest that temperature shocks can also affect overall inflation dynamics (Kotz et al., 2024; Faccia, Parker and Stracca, 2021; Ciccarelli, Kuik and Hernández, 2024; Mukherjee and Ouattara, 2021), mainly through a strong effect on food prices.

While the literature finds evidence for inflationary effects of temperature shocks, it has methodically focused on the impact of *local* weather fluctuations on *local* agricultural output or *local* food prices.³ This emphasis on local relationships is surprising, given the global nature of many food commodity markets. Many food commodities, such as wheat or corn, are traded globally and, thus, local supply and demand shocks spill over internationally. Moreover, panel models might underestimate the effect of local temperature anomalies. For most commodities, the top-producing countries account for a large share of global production (Table A.3), indicating that the impact of local temperature shocks on production and yields can differ strongly across countries, as pointed out in a simulation exercise by Chatzopoulos et al. (2020). Also, as Bilal and Känzig (2024) have recently shown, global temperature variation seems to be more closely related to extreme weather events than local temperature shocks. They conclude that analyses based on local temperature variations underestimate the true economic impact of temperature changes.

¹Food price changes can also have a disproportionately large effects on household inflation expectations (D’Acunto et al., 2021).

²The elasticities are taken from Roberts and Schlenker (2013)

³A notable exception in this context is De Winne and Peersman (2021), who discuss the adverse consequences of global harvest and weather disruptions on economic activity. The main focus of the paper, however, is to understand how weather-induced surges in global agricultural prices affect economic outcomes in initially unaffected regions, thereby concentrating on international spill-overs.

Against this background, we contribute to the existing literature by examining the impact of *global* seasonal temperature shocks on *global* food commodity prices and *global* food production quantities.

Using data from 1961 to 2023, we find strong effects of global temperature shocks that hit during northern hemisphere summer on global food commodity prices, which lasts for one to two years. The impact is particularly strong for grains, such as wheat or barley, but also present for several vegetable oils and meals. According to our estimates, a summer temperature shock of 0.4 °C, i.e. one which is approximately equal to the largest (northern hemisphere) summer shock in our data and similar to the ones observed in 2023 and 2024, comes with an economically significant rise of global food commodity prices by about 10 % within 12 months. The impact on global grain prices is even stronger. In contrast, temperature shocks happening in other seasons of the year appear to have no or only a marginal impact on global food prices. In our analyses, we use local projections to quantify the impact of global temperature shocks on global food commodity markets. To address the trending behavior of average temperature levels in the past decades, the global temperature shocks are constructed as deviations of global seasonal mean surface temperatures from their short-term average.

Additional results suggest that temperature shocks act as supply shocks on global commodity markets. Based on data on the global production of food commodities, we show that high temperatures in summer months reduce the globally produced quantity of food commodities considerably. A 0.4°C temperature shock in the summer months leads to a decline in the produced volumes of the items underlying the global food commodity price index by about 3 percent in the ongoing agricultural year. Again, the effects are particularly present for grains. In fact, our results indicate that summer temperature shocks act as supply shocks for most food commodities.

Our findings illustrate that global summer temperature shocks are a key driver of global food commodity developments. These insights are crucial for policymakers, economists, and stakeholders in the agricultural sector, as they highlight the importance of incorporating weather data into economic models and forecasts. Understanding the impact of seasonal temperature anomalies on food prices might help predicting inflation developments, formulating effective agricultural policies, and ensuring food security.

The paper is structured as follows: The next section describes the price data, the construction of temperature shocks and the estimation method. The third section presents the effects of temperature shocks on global commodity prices and is followed by section four, which focuses on the impact on produced quantities. The last section concludes.

2 Empirical Framework

2.1 Data

For the empirical analysis, the primary variables of interest are global food commodity prices as well as global seasonal temperature shocks. As our main food price variable we use a monthly food price index from the World Bank (2010 = 100, in USD, not seasonally adjusted), denoted as P_t^{Food} (see Figure A.1 in the Appendix). It covers various types of food commodities such as grains, fats, oils and other foods like meat, fruits or sugar. The index and most of its sub-components are available from January 1960 on. In the sample period, annual food price changes equal 3.3% on average and range from -56.66% to 79.84% (see Table A.1).

Our measure of seasonal temperature shocks is derived from monthly temperature anomaly data (in °C) taken from the UN Food and Agricultural Organization (FAO), which is available from January 1961 on (see Figure A.2). Those temperature anomalies are defined as global mean surface temperature deviations from their monthly long-term average (1951 to 1980). Based on those anomalies, monthly temperature shocks are derived as deviations of those monthly anomalies from their month-specific rolling 5-year average. This allows us to study how unexpected short-term temperature surprises, which are not expected by market participants (producers, consumers and traders), affect global food prices. We aggregate the monthly shocks to seasonal shocks by taking averages, i.e., for example, the summer temperature shock in a given year equals the average temperature shock of June, July and August in that year. This gives us for each season (spring, summer, autumn, winter) a time series starting in 1966 and ending in 2024. The seasons are defined according to their occurrence in the Northern Hemisphere.⁴ To reduce the impact of extreme values, we winsorize each seasonal series with the 5% and 95% value of the respective seasonal shock distribution. Figure 1 illustrates the seasonal temperature shocks in our sample (which starts in 1966 and ends in 2022). They are equal to 0.08 °C on average and range from -0.54 °C to 0.64 °C (see Table A.1). Winter seasons exhibit the highest volatility, whereas summer seasons seem to exhibit comparably small temperature shocks. In summer seasons temperature shocks did range from -0.26 °C to 0.36 °C.

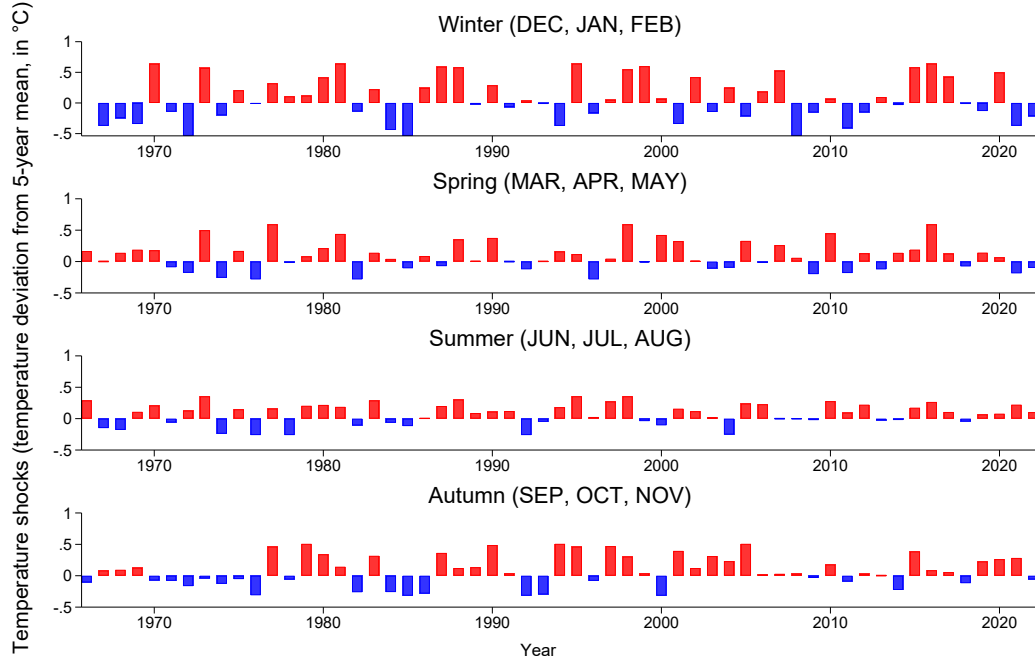
Figure A.3 in the Appendix shows that there is a positive correlation between summer temperature shocks and global food commodity price changes, which seems not to be driven by outliers.

2.2 Estimation Method

We use local projections to estimate the impact of seasonal temperature shocks on global food prices, as proposed by Jordà (2005), and as recently used by Bilal and Känzig (2024) to estimate the impact of global temperature surprises on economic output. In the base-

⁴Autumn consists of September, October and November, winter of December, January and February and spring of March, April, May.

FIGURE 1: Global seasonal temperature shocks



Notes: The figure shows annual global seasonal temperature shocks for the period 1966 to 2022. They represent deviations of seasonal temperature from their rolling 5-year mean (in °C). Red (blue) bars represent positive (negative) shocks.

line specification, we focus on the response of global food commodity prices h months after the seasonal shock hit. The analysis is conducted separately for each season $S \in [\text{spring, summer, autumn, winter}]$, with the primary focus on the summer months (June, July, and August) due to their importance for agricultural productivity.⁵

The main estimation equation reads as follows:

$$\ln(P_{t_S+h}) - \ln(P_{t_S-2}) = \alpha_{S,h} + \beta_{S,h} \text{TempShock}_{t_S} + \gamma_{S,h} \mathbf{X}_{t_S} + \varepsilon_{t_S+h}, \quad (1)$$

where $\alpha_{S,h}$ is a constant, P_{t_S} the food price index in period t_S and $\ln(P_{t_S+h}) - \ln(P_{t_S-2})$ the percentage change in food commodity prices between period $t_S + h$ and $t_S - 2$. Note that the frequency of the seasonal shocks is yearly, while the estimation horizon h varies by month. Period t_S always refers to the middle month of a season, i.e. April, July, October or January - depending on season S , and the shock TempShock_{t_S} is the corresponding seasonal temperature shock. We choose P_{t_S-2} as reference point, which corresponds to the last month of the previous season (i.e. before the shock hits). The coefficient $\beta_{S,h}$ captures

⁵ Alternatively, the impact of the seasonal temperature shocks can be estimated simultaneously in a unified specification in quarterly frequency, assigning a value of zero to shocks outside the relevant season. The results of this alternative specification are nearly identical to the seasonal specifications, see Figure A.13.

the impact of a temperature shock that hits in season S on the cumulative price response h months after the beginning of season S . To control for potential serial autocorrelation, in vector X_{ts} we add lags of the dependent variable and of the shock variable. The controls vary by season S and include the change in global food prices in the season of the previous year, as well as last year's seasonal temperature shock.⁶ To compute confidence bands, we follow the lag-augmented approach by Montiel Olea and Plagborg-Møller (2021).

3 Empirical Results

3.1 Effect of temperature changes on food commodity prices

3.1.1 Main Results

Figure 2 contains the main estimation results. They show that summer temperature shocks have a significant effect on global food commodity prices. In contrast, temperature shocks in winter, spring or autumn seem to have no such significant effect on global food prices.⁷ Food commodity prices rise instantly if summer temperatures are above their rolling 5-year average and remain elevated for more than one year. According to the estimates, a summer temperature shock of 0.4°C would result in a rise of food prices by about 10% within twelve months.

3.1.2 Heterogeneity of food price effects

In addition, the analysis reveals a large heterogeneity in food price reactions. In particular prices of grains such as barley, corn, rice, sorghum and wheat react strongly to summer temperature shocks (see Figure 3). Figure A.5 shows that this is the case for each single grain type covered by our data set. Prices of oils and meals overall also react significantly. This is particularly the case for soya oil, coconut oil, groundnut oil and palm oil (Figure A.5), whereas the effect on the remaining components of this food category is more muted. Prices of the category “other foods”, which contains for example meat and sugar, does not seem to react at all. For some of them, such as cocoa, sugar or coffee prices, we even find negative price effects of positive temperature shocks.⁸

3.1.3 Robustness checks

The main finding is robust to a variety of alternative assumptions:

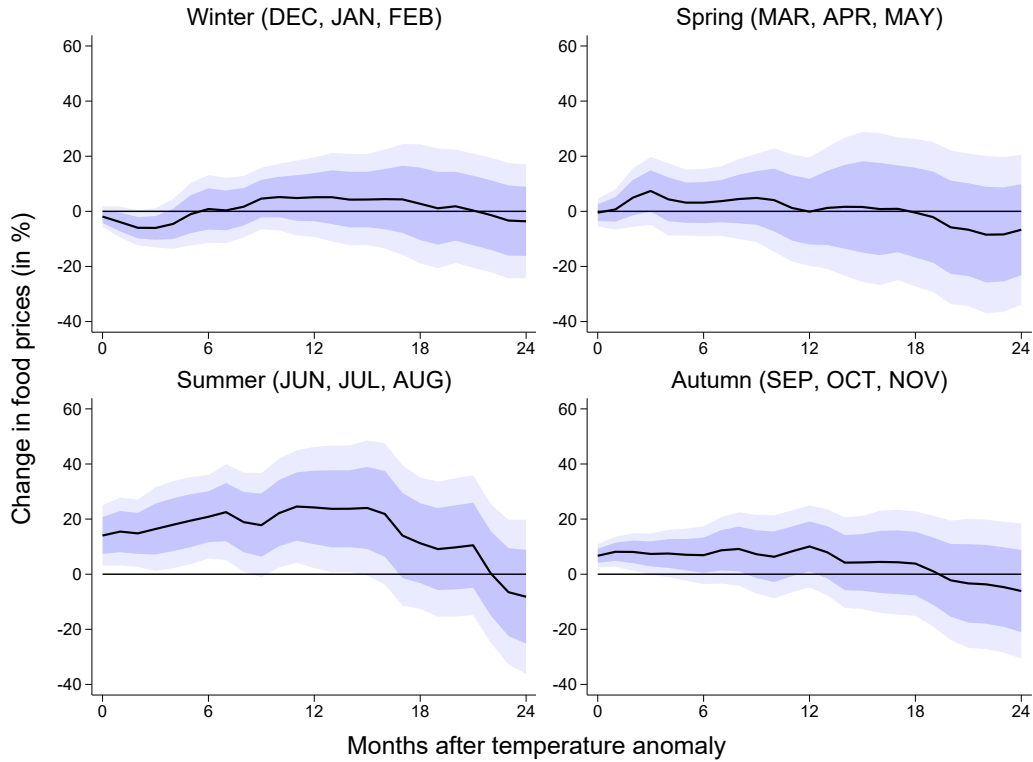
- *Alternative price measures:* Figure A.8 in the Appendix illustrates that the finding is robust to the use of alternative food price measures. We use four alternative food

⁶The seasonal shocks show little autocorrelation over time, see Figure A.4.

⁷For autumn, there is some evidence of a positive effect. However, compared to summer temperature shocks, autumn temperature shocks appear economically and statistically clearly less significant.

⁸The World Bank provides prices for beverages (coffee, cocoa and tea) but does not include them into their food price index.

FIGURE 2: Impact of seasonal temperature shocks on global food commodity prices

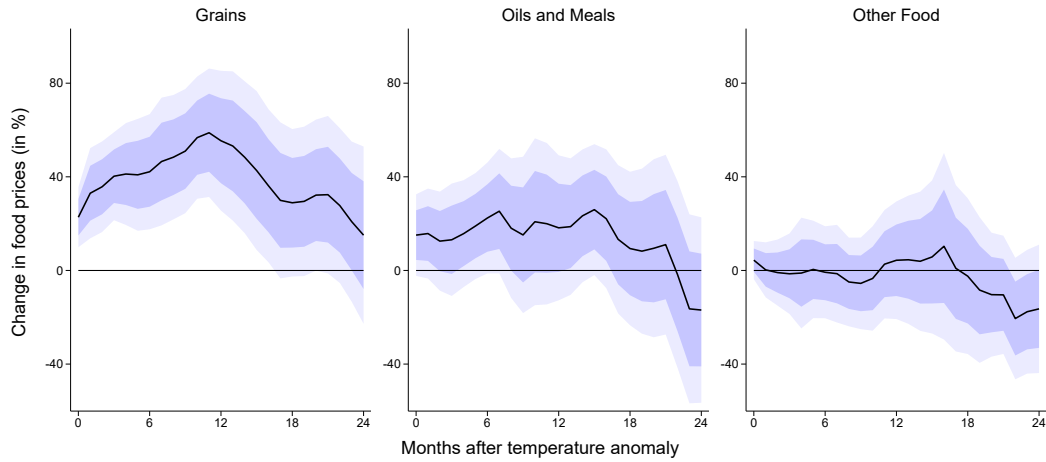


Notes: Cumulative impulse responses to seasonal temperature shocks (of 1 °C) using the baseline local projection specification. Shaded areas represent 68% and 90% confidence intervals. Horizon 0 corresponds to the middle month of the respective season.

commodity price measures, which all differ in their composition of underlying food prices: (1) IMF food commodity price index (which covers more types of food than the World Bank indicator but is available only from 1992 on), (2) HWWI food commodity price index (which covers less types of food and starts only in 1970), (3) FAO food price index (which covers the most types of food but only starts in 1990) and (4) the CRB price index for foodstuffs (which starts in 1960 but covers nowadays only very few food commodities). Despite their different properties, for all four indices we find qualitatively similar results as with our main food price variable: positive global summer temperature shocks result in longer-lasting, significantly elevated food commodity prices.

- *Alternative temperature measures:* In a similar vein, using alternative measures of temperature shocks also corroborates our main findings (see Figure A.9). Instead of using temperature deviations from their 5-year average, deviations from 10-year or from 3-year averages yield very similar results as our baseline specification. In addition,

FIGURE 3: Impact of summer temperature shocks on subgroups of food commodity prices



Notes: Cumulative impulse responses to temperature shocks in summer (of 1 °C) using the baseline local projection specification. Shaded areas represent 68% and 90% confidence intervals. Horizon 0 corresponds to the middle month of the season (July).

two more specifications use alternative temperature data, one from the U.S. NOAA, covering global land surface temperature anomalies, and one from the EU Copernicus service, covering global two meters surface temperature anomalies.⁹ Both support the baseline conclusions.

- *Sample splits and the pandemic:* To understand whether the effects differ between different sub periods, in a robustness check, we split our sample into two periods: 1966 to 1993 and 1994 to 2022. Figure A.10 shows that we find for both qualitatively similar results as with our baseline specification. Looking at the main food categories, we find strongly significant effects for grains for both sub periods. In contrast, the impact of summer temperature shocks on oils and meals is only significant in the latter period. For other food we find mostly insignificant effects. Another concern could be the effect of the pandemic and the Russian war against Ukraine, which both had a strong impact on global food prices. Excluding those years, we continue to find a significant positive effect of similar size (Figure A.11), corroborating our baseline findings.
- *Alternative specifications:* Weather conditions might be correlated across seasons. For example, a hot summer might be followed by a warm autumn. To account for potentially correlated seasonal temperature shocks, we estimate several alternative specifications. The positive food price response after a summer temperature shock is robust if we include all seasonal temperature shocks from the past four seasons, if we add the seasonal temperature shocks in the upcoming four seasons or including both, i.e.

⁹Retrieved from [ClimateReanalyzer.org](https://climate.reanalyzer.org) and based on ECMWF ERA5.

all seasonal temperature shocks from summer of the last calendar year to summer of the upcoming year (Figure A.12). In addition, the results are also hardly affected if the effects of the seasonal temperature shocks are estimated simultaneously in a specification in quarterly frequency, in which a value of zero is assigned to shocks outside the relevant season (Figure A.13).¹⁰

- *Regional seasonality:* The summer temperature shock used in the main analysis reflects the season in the northern hemisphere (NH). Using this global summer metric disregards that the NH summer is accompanied by winter in the southern hemisphere (SH). We account for this regional heterogeneity by studying seasonal temperature shocks for both hemispheres separately. Specifically, here, the global temperature shock for the NH summer in equation (1) is replaced by shocks that either capture temperature shocks between June and August in the NH or in the SH.¹¹ Accounting for this regional heterogeneity shows that NH summer temperature shocks drive the positive global food price response found in the main analysis (Figure A.14). In particular, elevated temperatures during the NH summer lead to a significant increase in global food prices - of a similar size as found in the baseline estimation. Temperature shocks happening in the SH summer, spanning from December to February, on the contrary, hardly affect global food commodity prices. The results are in line with the global distribution of food production. The vast majority of the largest food producers are located in the northern hemisphere (Table A.3). This is particularly the case for most grains, the group of commodities we found to be most sensitive to temperature fluctuations.

4 Effect of temperature changes on food production

To shed light on the reasons for the positive effect of summer temperature shocks on global food commodity prices, in a next step, we focus on the impact of high temperatures in summer on food production. In principle, the significant reaction of food prices to summer temperature shocks can be driven by supply or demand factors. It seems likely, however, that high temperatures affect food prices through their detrimental impact on the quantity of produced (or harvested) food products.

We test the hypothesis that temperature shocks act as supply shocks for food commodities in an additional regression analysis. As above, we use local projections to quantify the impact of the temperature shock, but focus solely on the summer months.¹² Data on

¹⁰Note that effects of the seasonal temperature shocks on the subgroups of food commodities (grains, oils and meals and other food) as well as single foods or the robustness exercises above also remain nearly unchanged if the seasonal impacts are estimated simultaneously (results are available upon request).

¹¹The underlying data is taken from the National Oceanic and Atmospheric Administration (NOAA), which publishes data on regional temperature anomalies. We add the temperature shock in the other hemisphere to the set of control variables to account for potential contemporaneous correlation of weather conditions across hemispheres.

¹²We show the results for the other seasons in robustness exercises, see Figure A.7

produced quantities are only available on yearly frequency and we adjust the regression accordingly. Specifically, we regress the (cumulative) change in food production in the current and next agricultural year on the summer temperature shock, which equals the shock used in the price regressions. Importantly, the estimation horizon $h \in [0, 1]$ now corresponds to one year. The adjusted estimation equation is the following:

$$\ln(Q_{\tau+h}) - \ln(Q_{\tau-1}) = c_h + \lambda_h TempShock_\tau + \theta_h X_\tau + \epsilon_{\tau+h}, \quad (2)$$

where Q_τ corresponds to the production of food in the current agricultural year and $TempShock_\tau$ to the temperature shock in summer of the current agricultural year. We additionally include one lag of the shock and the dependent variable in vector X_τ and a constant c_h .

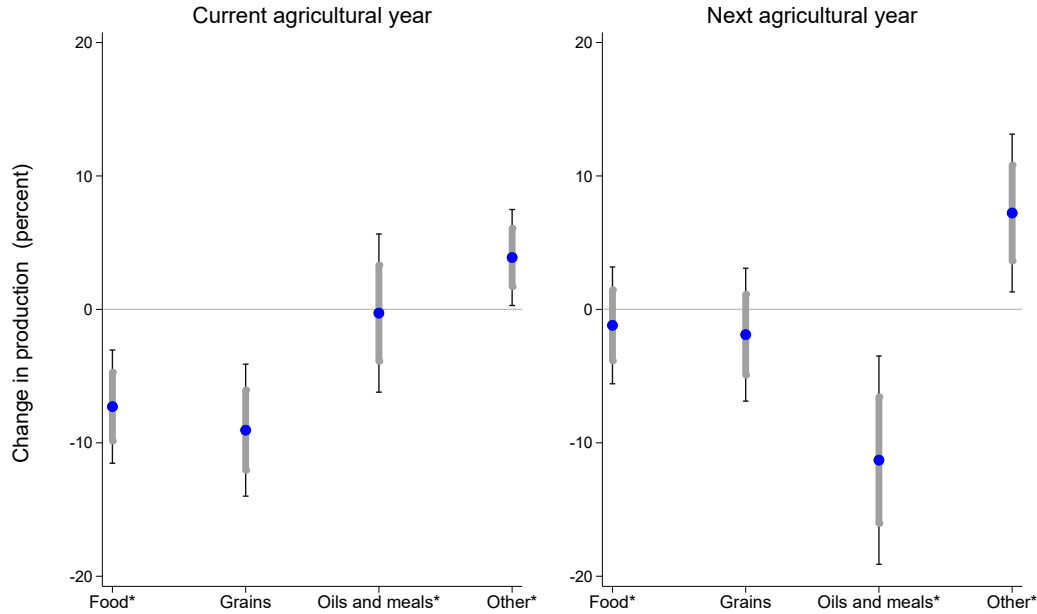
For the analysis, we use data on the globally produced quantity (in mt) of a large number of food items in an agricultural year from 1960 to 2023, provided by the United States Department of Agriculture (USDA). We deliberately use data for the agricultural rather than the calendar year. The former spans from May of the current year until April of the next calendar year. Data for the agricultural year is, hence, better suited to capture the effect of a temperature shock that hits in the summer months. For our main analysis, we sum up individual production series to generate aggregates for food, grains, oils and meals as well as other foods. The food items that are included in the respective aggregates are closely aligned with the products whose prices enter the respective price indices used in the price regressions (see Table A.2). However, due to data constraints, the aggregate for oils and meals differs slightly from its price counterpart, while the aggregate for other foods differs more strongly.¹³ The estimation sample covers the years 1966 to 2023.

Figure 4 shows the estimated responses of the food production index as well as the production indices for the three subgroups, grains, oils and meals, and other food. In the initial agricultural year, the production of food decreases significantly in response to a positive summer temperature shock.¹⁴ The response is mainly driven by a negative effect of higher temperatures on the production of grains, which contracts markedly. A temperature shock of 0.4°C in summer leads to a reduction in the production of food and grains in the initial agricultural year of 2.9% and 3.6%, respectively. In line with the price estimates, for other seasons we find no significant effect of seasonal temperature shocks on food production quantities, except for grain production in spring, see Figure A.7. The contraction in produced quantities due to summer temperature shocks is widespread over different types of grains (see Table 1 and Figure A.6). The findings are in line with our hypothesis: A positive temperature shock in the summer months leads to a decline in grain production and, inter alia, an increase in prices for grains. The food composite responds accordingly. Hence, in the initial agricultural year, the temperature shock resembles a

¹³The production of oils and meals includes seven out of the nine products in the respective price index. The production aggregate for other food comprises data for sugar, beef and oranges, while the respective price index additionally includes prices of chicken and lamb meat, bananas as well as shrimp (see Table A.2).

¹⁴The results are robust in specifications that exclude the pandemic, see Figure A.15.

FIGURE 4: Impact of summer temperature shocks on global food production quantities



Notes: Cumulative impulse responses of produced quantities to summer temperature shocks (of 1 °C), including 68% and 90% confidence intervals. An agricultural year spans from May to April, i. e. the current agricultural year covers the period from May in the calendar year of the temperature shock to April of the subsequent calendar year. *Aggregates for food, oils and meals as well as other food differ in part from the respective price indices due to data limitations. See appendix for details.

supply shock. For grains and the food composite, the shock is of temporary nature. In the subsequent agricultural year the impulse responses of the production indices for grains as well as the total food composite become insignificant.

The aggregate indices for the production of oils and meals do not respond significantly to the temperature shock in the initial agricultural year. In the next agricultural year, the production index for oil and meal products shows a significant decline. Looking at the individual products underlying the index, the picture becomes more mixed (see Figure A.6 and Table 1). The production of some oils (coconut and palm oil) already contracts in the initial year, while produced quantities of particularly soy products show a significant decline with a delay. The comparison between the effects on produced quantities and on prices for oils and meal products (Table 1) confirms the supply shock nature of the temperature shock. Overall, most prices increase and their quantities decline in reaction to positive summer temperature shocks.

In contrast, the production of other foods shows a significant increase in reaction to summer temperature shocks in the current and next agricultural year. This response is caused by a significant increase in the production of sugar (Figure A.6). The observation is partly in line with the price reaction of sugar, which shows a significant decrease at the end

TABLE 1: Comparison between price and quantity reaction of different food products.

	Prices		Quantities	
	Current agricultural year	Next agricultural year	Current agricultural year	Next agricultural year
Grains				
Barley	+	+	-	-
Corn	+	+	-	
Rice	+	+		+
Sorghum	+	+	-	
Wheat	+	+	-	
Oils and meals				
Soy beans		+		-
Palm oil	+	+	-	
Coconut oil	+	+	-	
Soy oil	+	+		-
Soybean meal	+			-
Oilseed copra	+	+	-	
Fishmeal	+			
Other food				
Meat				
Sugar		-	+	+
Coffee	-	-		+

Notes: Only includes products for which estimates for both, prices and quantities, are available. Cells are marked if effect is significant at 68% for at least one month within the given time frame. For the price response, the current agricultural year covers horizons 0 to 9 (in Figure A.5), which corresponds to July of the current calendar year to April of the next calendar year. The next agricultural year comprises horizons 10 to 21 (May to April).

of the estimation horizon (see Figure A.5). Compared to the price index, sugar production has a stronger weight in the production index of other foods, which only comprises three out of the seven series that are included in the respective price index, see Table A.2. This can explain why the production index of other foods increases one year after the summer temperature shock, while the respective price index shows no corresponding response.

The overwhelmingly mirrored reaction of prices and quantities of individual products supports the hypothesis that summer temperature shocks act as supply shocks. Table 1 summarizes the responses of production quantities and prices of individual products in the

first and second agricultural year after a summer temperature shock. For the vast majority of products, we find an increase of prices and a corresponding decrease in produced quantities.¹⁵

5 Conclusion

This paper provides compelling empirical evidence of the significant impact of seasonal temperature shocks on global food commodity prices. In particular, summer temperature shocks lead to an elevated positive response of global food commodity prices within the first two years after the shock. At the same time, produced quantities of food commodities decline after a positive temperature shock in the summer months - highlighting that temperature shocks act as supply shocks on global commodity markets. The results also show that prices and produced quantities of various types of grains such as wheat, corn or barley, and some vegetable oils, are particularly responsive to summer temperature anomalies. The majority of the individual products studied, show rising prices and reduced production after the summer temperature shock, with the exception of some particular goods, like coffee or cocoa, whose prices decline. The findings underscore the importance of considering climatic factors in understanding and forecasting commodity price movements.

Future research could further explore the mechanisms behind these relationships, as well as the potential impacts of other climatic factors on global food commodity prices. Policymakers and stakeholders in the agricultural and commodity trading sectors could also benefit from these insights in their decision-making processes, particularly in the context of climate change mitigation and adaptation strategies.

¹⁵For coffee and sugar, higher temperatures act as a positive supply shock with production increasing and prices decreasing. Only for some products, such as fishmeal, meat and rice, higher temperatures do not seem to affect quantities and prices in a supply shock way.

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A Additional Results

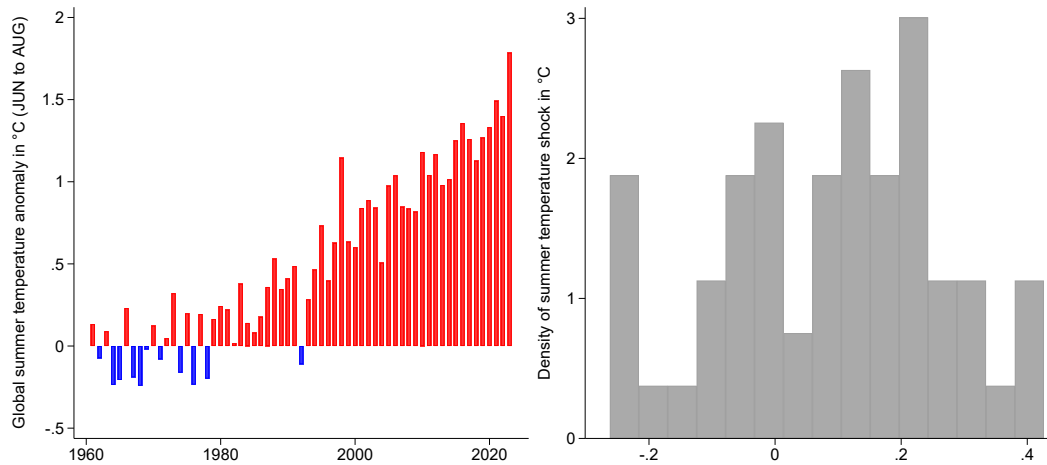
A.1 Descriptive Evidence

FIGURE A.1: Food commodity price index



Notes: The figure shows the monthly World Bank food commodity price index (2010 = 100, in USD).

FIGURE A.2: Global summer temperature anomalies and shocks



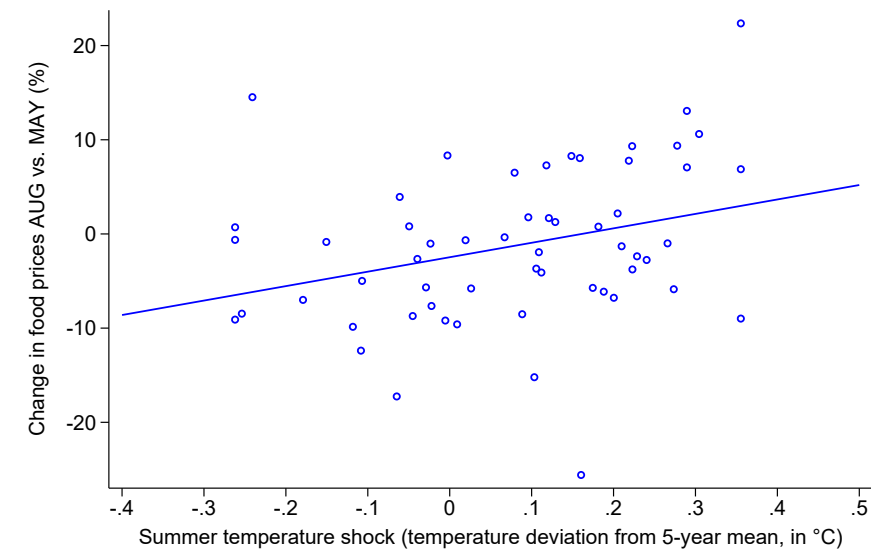
Notes: The left figure shows annual global summer temperature anomalies for the period 1961 to 2023 taken from the UN Food and Agriculture Organization (FAO). Temperature anomalies here are defined as global mean surface temperature deviations for the summer months (average for June, July and August) from their long-term average (1951 to 1980). Red bars represent positive anomalies, blue bars represent negative anomalies. The right figure shows the distribution of summer temperature shocks, constructed as the deviation of temperature anomalies from their 5-year mean, in °C, 1966-2023.

TABLE A.1: Summary Table

	Season	N	$Mean$	SD	$Min.$	$Max.$
<i>Temperature anomaly (monthly frequency):</i>						
$Temp_t$	Winter	56	0.08	0.36	-0.54	0.64
	Spring	57	0.09	0.23	-0.28	0.59
	Summer	57	0.08	0.17	-0.26	0.36
	Autumn	57	0.08	0.25	-0.32	0.51
<i>Price indices (monthly frequency): $\ln P_{t_s}^i - \ln P_{t_s-2}^i$</i>						
$\Delta \ln P_{t+12}^{Food}$	Winter	56	4.98	18.95	-56.66	69.95
	Spring	57	3.70	16.59	-26.35	51.88
	Summer	57	2.01	19.63	-33.87	79.84
	Autumn	57	2.52	17.65	-35.96	60.54
<i>Production (yearly frequency): $\ln Q_\tau^i - \ln Q_{\tau-1}^i$</i>						
grains		58	2.13	4.29	-4.82	11.38
oils and meals		58	4.54	5.69	-6.74	28.96
other food		58	1.83	3.44	-7.48	8.08
food		58	2.27	3.67	-4.69	10.27
barley		58	0.75	7.89	-20.86	20.08
corn		58	2.93	8.13	-23.33	27.44
rice		58	1.91	2.76	-5.54	8.54
sorghum		58	0.40	9.15	-19.08	23.25
wheat		58	1.92	5.98	-9.22	16.12
soy beans		58	4.38	10.62	-19.93	46.18
palm oil		58	7.04	5.61	-10.64	16.89
coconut oil		58	1.07	11.15	-22.00	30.09
soybean oil		58	4.72	7.05	-12.70	34.36
soy meal		58	4.55	6.85	-10.61	34.38
copra		58	1.04	10.65	-22.32	32.22
fishmeal		58	0.48	10.85	-31.58	26.85
meat (beef)		58	1.31	2.45	-5.49	8.43
sugar		58	1.90	5.09	-12.67	12.96
coffee		58	1.23	11.00	-26.02	26.20
oranges		58	2.47	8.85	-16.33	25.85

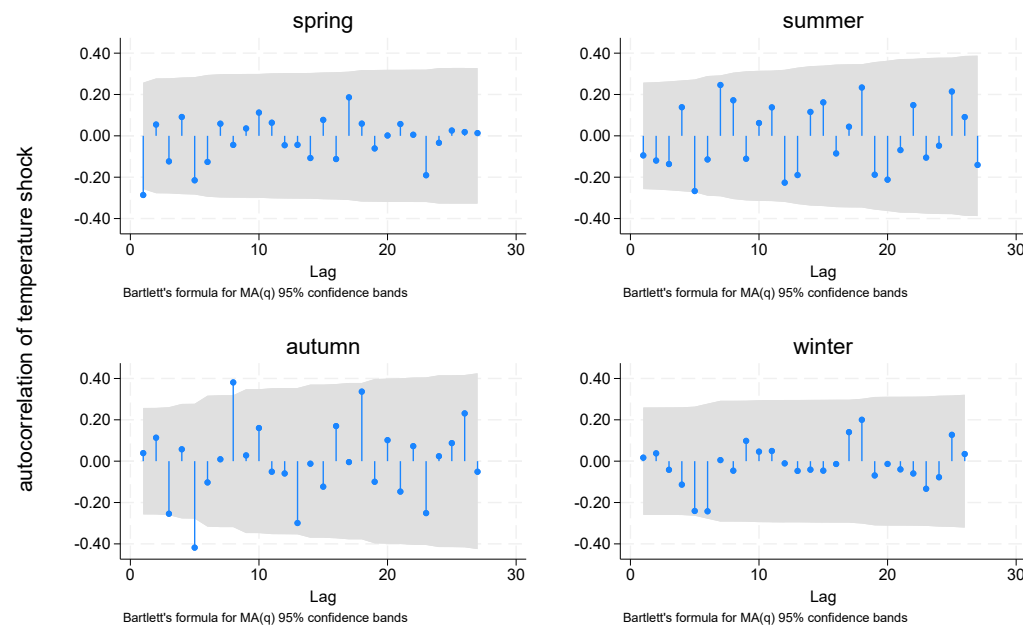
Notes: Summary statistics for the sample spanning from 1966 to 2023 for production data and 1966 to 2022 for prices.

FIGURE A.3: Correlation between summer temperature shocks and food commodity prices



Notes: Correlation between global summer temperature shocks (in °C) and food commodity price changes between May and August of the same year (in %).

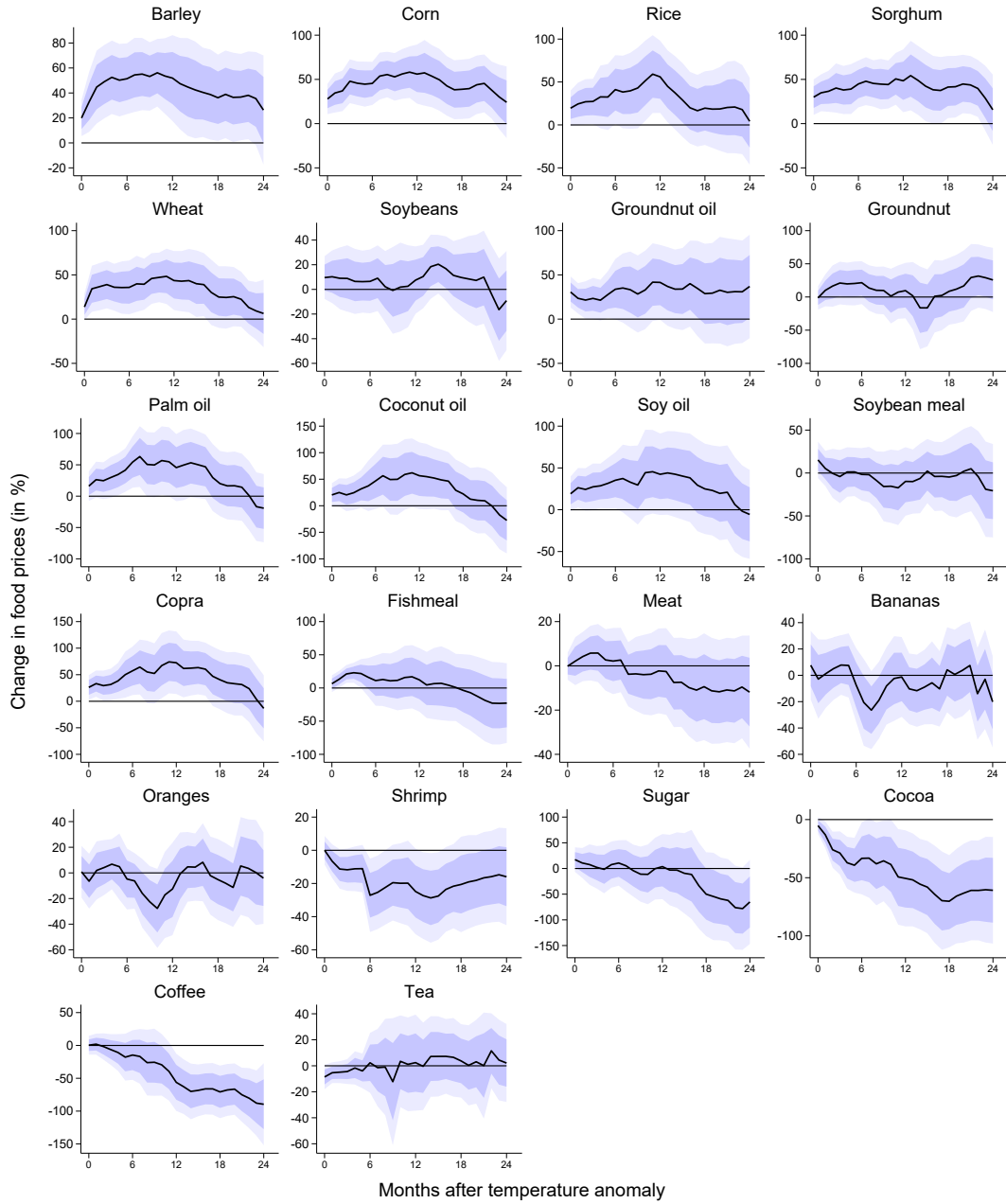
FIGURE A.4: Autocorrelation of the temperature shocks of different seasons



Notes: Autocorrelation of seasonal temperature shocks at different lags (years).

A.2 Additional Estimation Results

FIGURE A.5: Effects on single foods



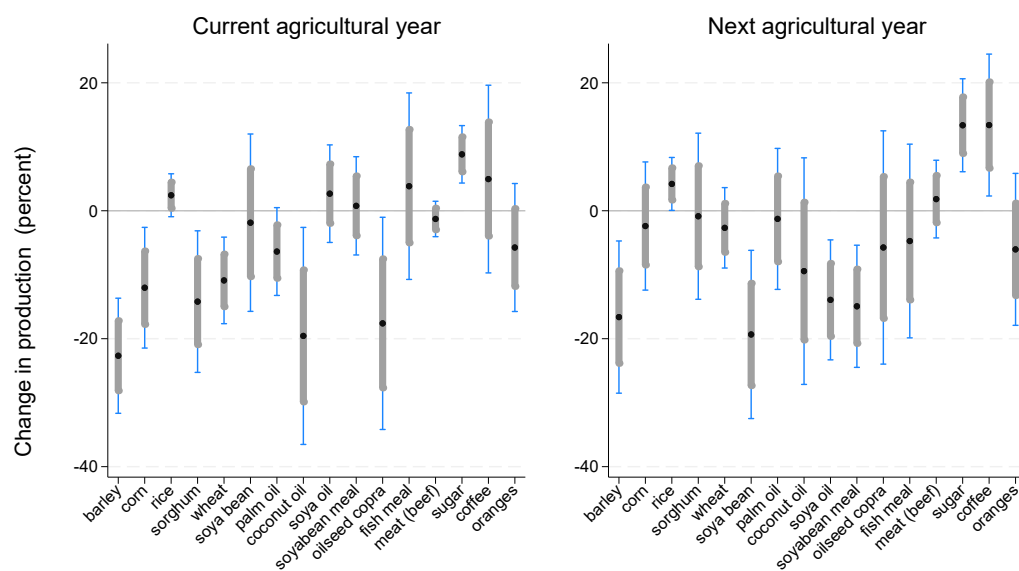
Notes: Cumulative impulse responses to a temperature shock in the summer months (of 1°C) using the baseline local projection specification for single foods. Shaded areas represent 68% and 90% confidence intervals. Horizon 0 corresponds to the middle month of the season (July).

TABLE A.2: Comparison between prices indices and production aggregates

	Price indices (World bank)	Quantities (USDA)
Grains	Barley	Barley
	Rice	Rice
	Corn	Corn
	Sorghum	Sorghum
	Wheat	Wheat
Oils and Meals	Coconut oil	Coconut oil
	Fish meal	Fish meal
	Palm oil	Palm oil
	Palmkernel oil	Palmkernel oil
	Soybean meal	Soybean meal
	Soybean oil	Soybean oil
	Soybeans	Soybeans
	Groundnuts	
	Groundnuts oil	
Other food	Beef	Beef
	Oranges	Oranges
	Sugar	Sugar
	Chicken	
	Lamb	
	Bananas	
	Shrimp	

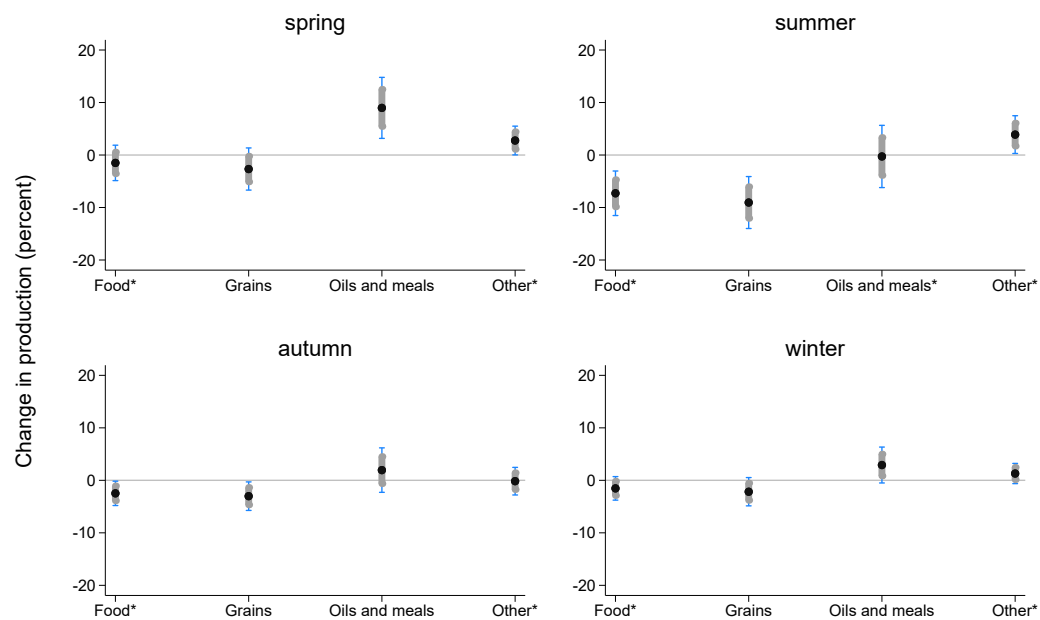
Notes: Price indices according to the World Bank Commodity Price Index. Aggregates for food production are generated in a way to match the composition of the price indices as closely as possible using data on the production in thousand metric tons of individual food items from the United States Department of Agriculture (USDA).

FIGURE A.6: Effects on single foods



Notes: Cumulative impulse response of produced quantities of different food products to a summer temperature shock (of 1 °C), including 68% and 90% confidence intervals. The current agricultural year spans from May of the current to April of the next calendar year.

FIGURE A.7: Effect on produced quantities in current agricultural year to temperature shock in different seasons

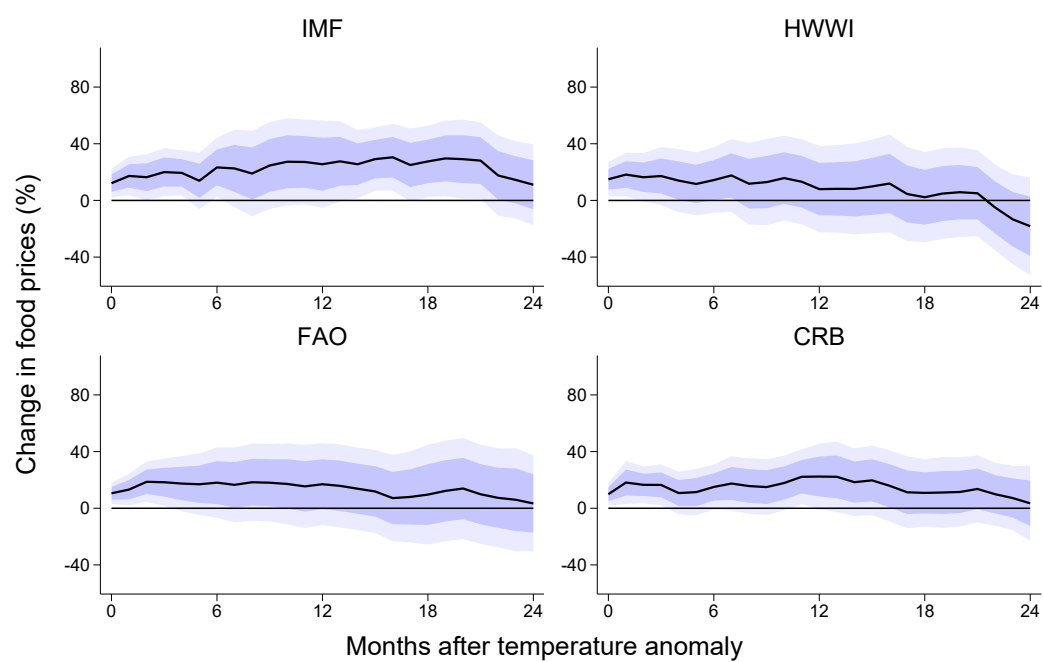


Notes: Cumulative impulse response of produced quantities of food aggregates to a seasonal temperature shock (of 1°C), including 68% and 90% confidence intervals. The current agricultural year spans from May of the current to April of the next calendar year.

A.3 Results of robustness exercises

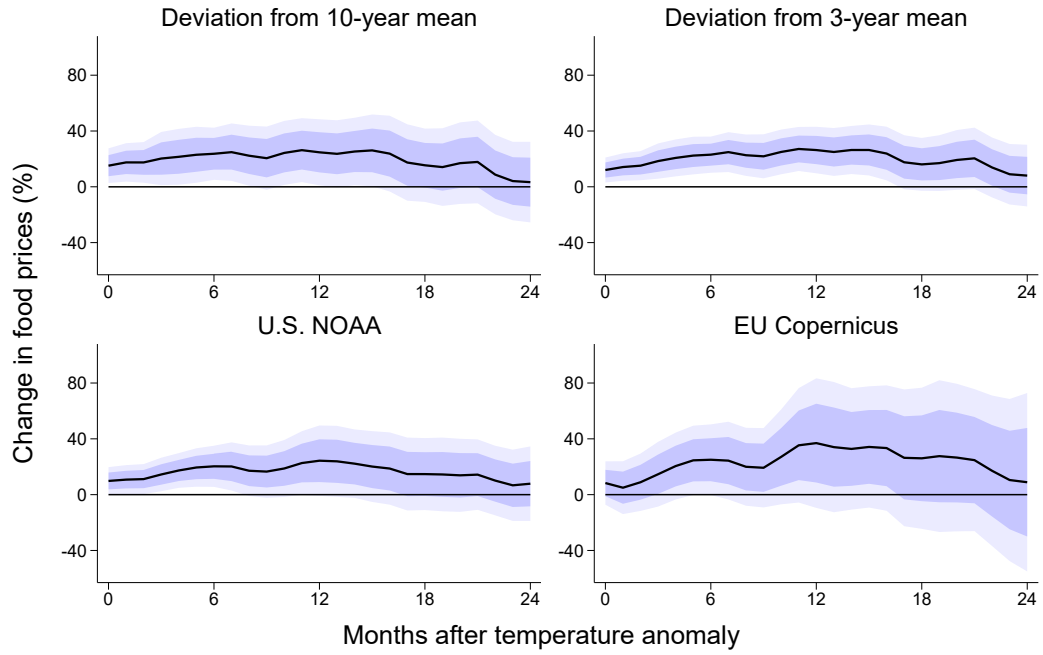
A.3.1 Price regressions

FIGURE A.8: Alternative price measures



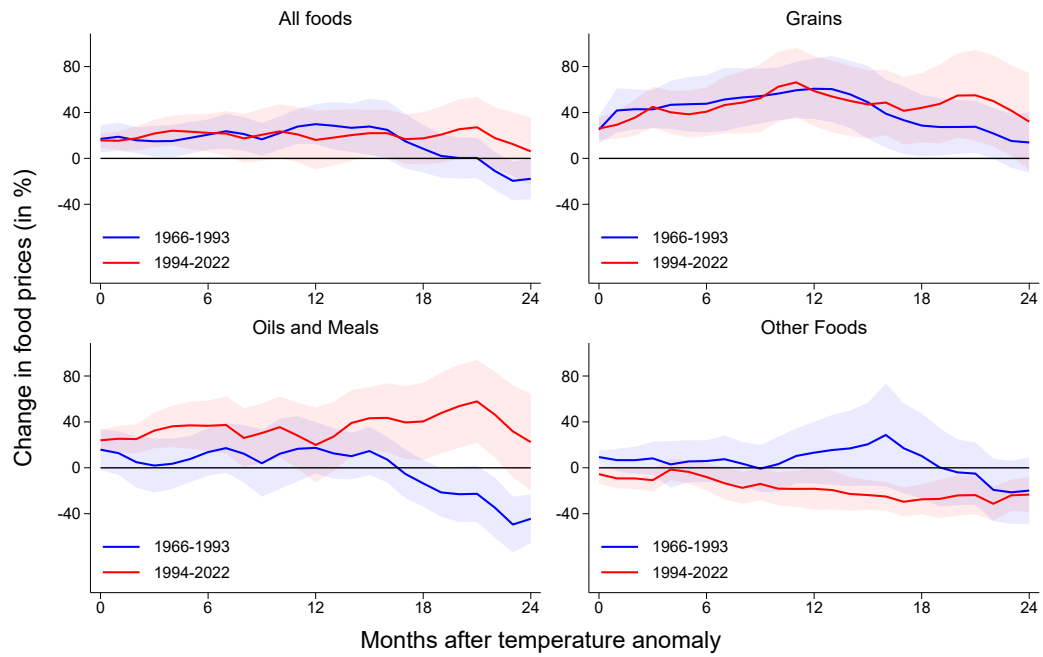
Notes: Cumulative impulse responses to summer temperature shocks (of 1°C) using the baseline local projection specification but with alternative food commodity price measures: (1) IMF food price index, (2) HWWI food price index, (3) FAO food price index, (4) CRB price index for foodstuffs. Shaded areas represent 68% and 90% confidence intervals. Horizon 0 corresponds to the middle month of the season (July).

FIGURE A.9: Alternative temperature measures



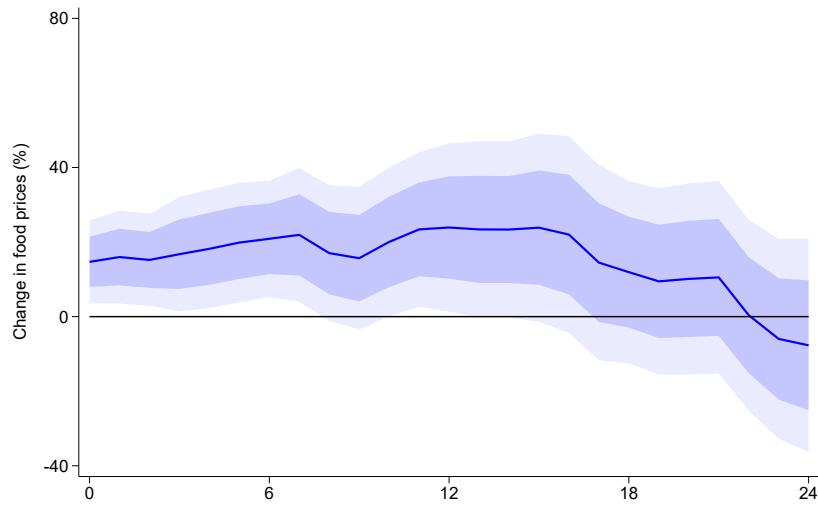
Notes: Cumulative impulse responses to summer temperature shocks (of 1°C) using alternative temperature measures: (1) deviation of the 10-year temperature mean, (2) deviation of the 3-year temperature mean, (3) deviation of the 5-year temperature mean and with U.S. NOAA temperature data, (4) deviation of the 5-year temperature mean and with EU Copernicus temperature data. Shaded areas represent 68% and 90% confidence intervals. Horizon 0 corresponds to the middle month of the season (July).

FIGURE A.10: Sample splits



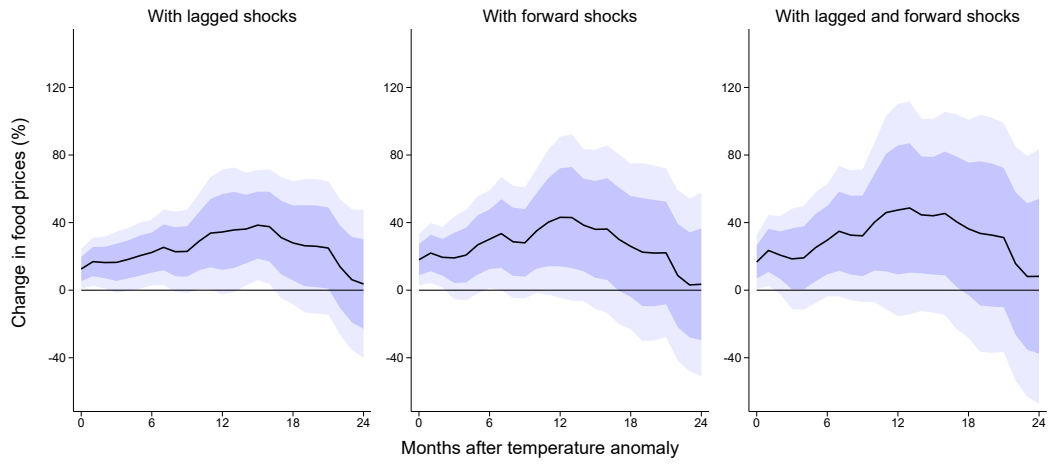
Notes: Cumulative impulse responses to summer temperature shocks (of 1°C) for two subsamples: 1966 to 1993 and 1994 to 2022. Shaded areas represent 68% confidence intervals. Horizon 0 corresponds to the middle month of the season (July).

FIGURE A.11: A sample without the pandemic period (ending in 2017)



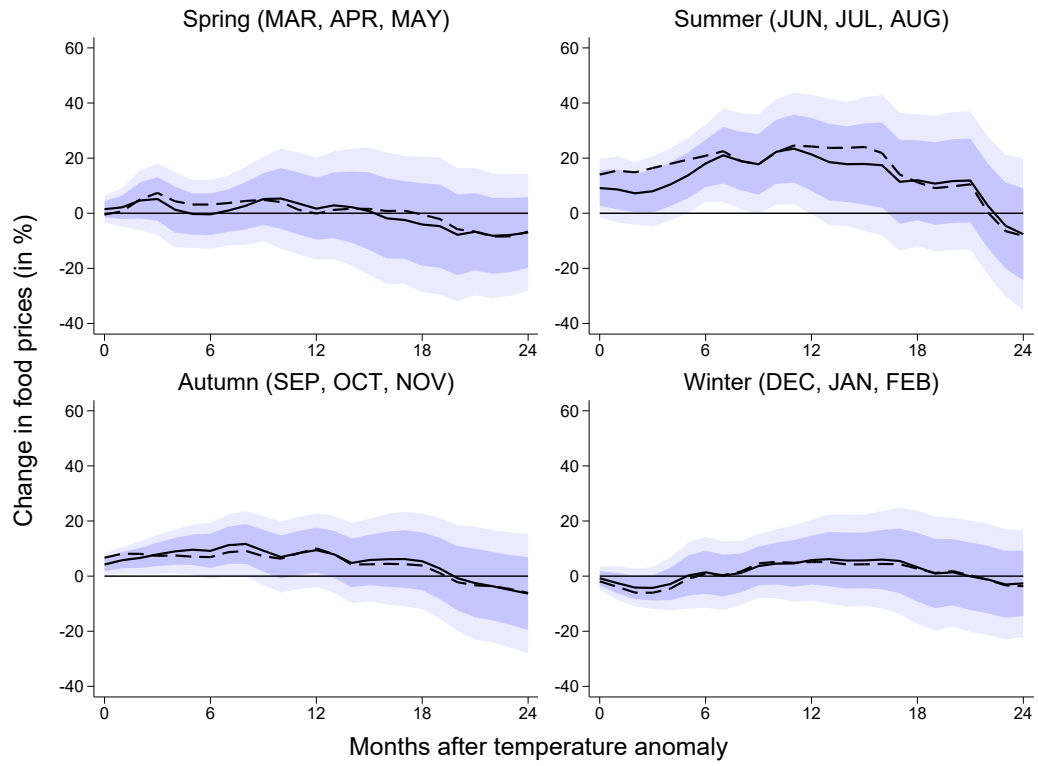
Notes: Cumulative impulse response to summer temperature shocks (of 1°C) for an alternative sample which ends in 2017 to exclude the pandemic period and the Russian war against Ukraine. Shaded areas represent 68% confidence intervals. Horizon 0 corresponds to the middle month of the season (July).

FIGURE A.12: Alternative specifications



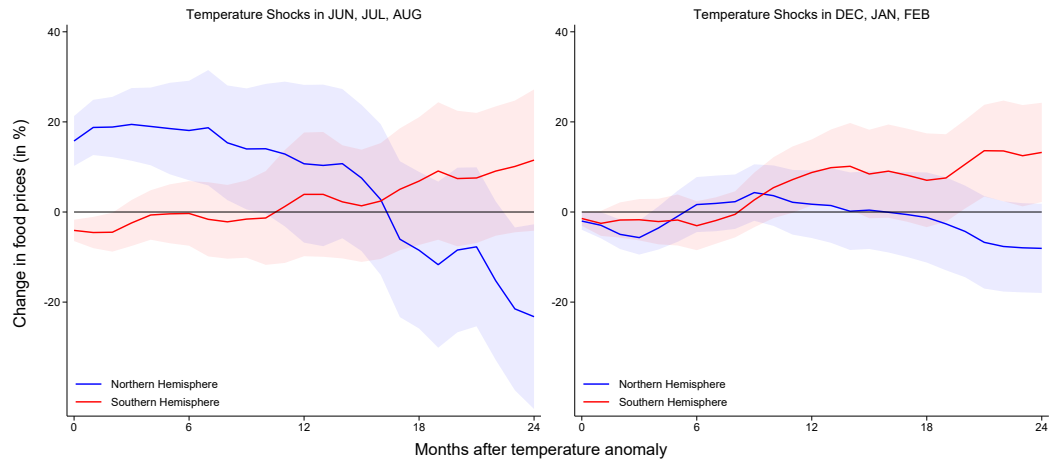
Notes: Cumulative impulse responses to summer temperature shocks (of 1°C) for alternative specifications: (*left*) including three lagged seasonal temperature shocks (spring, winter and autumn), (*middle*) including three forward shocks (autumn, winter and spring) or (*right*) including both. Shaded areas represent 68% and 90% confidence intervals. Horizon 0 corresponds to the middle month of the season (July).

FIGURE A.13: Simultaneous estimation of seasonal responses



Notes: Cumulative impulse responses to seasonal temperature shocks (of 1°C) for the baseline specification (dashed line) and a specification in which the impulse responses of different seasons are estimated simultaneously (solid lines and respective 68% and 90% confidence intervals). The latter specification is estimated in quarterly frequency and includes the shocks of all four seasons (and 12 month lags), assigning a value of zero to shocks outside the relevant season.

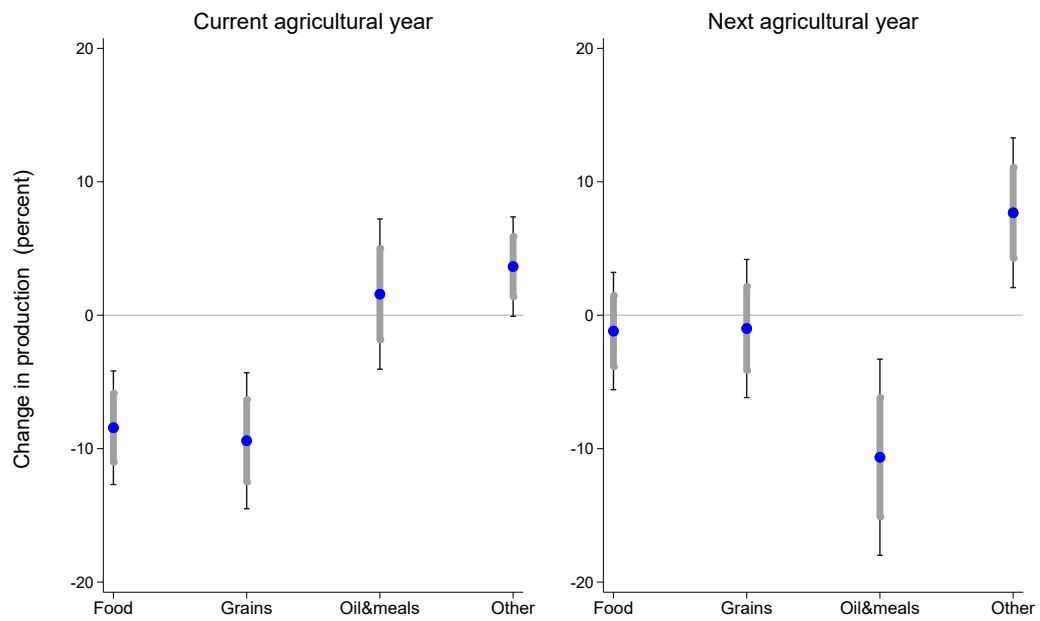
FIGURE A.14: Regional heterogeneity



Notes: Cumulative impulse responses to summer (June to August) and winter (December to February) temperature shocks (of 1°C) in the northern hemisphere and the southern hemisphere on global food commodity prices. Shaded areas represent 68% confidence intervals. Horizon 0 corresponds to the middle month of the season (July, January).

A.3.2 Production regressions

FIGURE A.15: Response in current agricultural year in a sample without the pandemic period (ending in 2018)



Notes: Cumulative impulse responses to summer temperature shocks (of 1°C) for an alternative sample which ends in 2018 to exclude the pandemic period, including 68% and 90% confidence intervals.

TABLE A.3: Three largest producer of global food commodities

Commodity	Three largest producer (average 1993 to 2023)	Share in total production (average)
Barley	Russian Federation, Germany, France	27.4
Rice	China, India , Indonesia	59.7
Corn	USA, China , Brazil	63.9
Sorghum	USA, Nigeria, India	38.9
Wheat	China, India, USA	38.2
Coconut oil	Philippines , Indonesia, India	76.5
Fish meal		
Palm oil	Indonesia, Malaysia, Thailand	86.4
Palm kernel oil	Indonesia, Malaysia, Nigeria	85.7
Soybean meal		
Soybean oil	USA, China , Brazil	60.4
Soybeans	USA , Brazil, Argentina	79.6
Groundnuts	China, India, Nigeria	60.6
Groundnuts oil	China, India, Nigeria	70.1
Beef	USA, China , Brazil	41.1
Oranges	Brazil, USA, China	47.8
Sugar cane	Brazil, India, USA	61.7
Chicken	USA, China , Brazil	43.2
Lamb	China , Australia, New Zealand	33.6
Bananas	India, China, Nigeria	36.9
Shrimp		

Notes: The table shows the three largest provider for the respective food commodity over the period 1993 to 2023 (taking the average of total production over this period as reference) and the average share of these countries in total production over the same horizon, according to the crop and livestock statistics by the Food and Agriculture Organization of the United Nations (FAO). We choose 1993 as starting point to exclude the Soviet Union. The database do not contain information for meals or shrimp. Countries that are fully located in the northern hemisphere are highlighted in bold.