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Temperature, Precipitation and Food Price Inflation: Evidence from a Panel of Countries

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Abstract

This study addresses a significant gap in the existing literature by examining the association between weather variables, i.e. temperature and precipitation, and food price inflation at monthly frequency. Using a comprehensive panel dataset that spans 23 years of data for 186 countries, we explore this relationship in depth. Furthermore, we employ panel quantile regression techniques to investigate how weather-related variables influence food price inflation across different quantiles of inflation. Our findings reveal three key results. First, we establish that weather variables play a crucial role in explaining inflation, with temperature generally having a negative coefficient with inflation contemporaneously. In contrast, precipitation appears to have a positive coefficient, and the strength of these associations varies across different inflation quantiles. In addition, although the contemporaneous effect is negative, the cumulative inflationary effect of 1°C temperature increase reaches up to 0.6 percentage points. Subsequently, our results demonstrate sensitivity to the method of clustering the panel of countries, indicating the importance of methodological considerations in such analyses.

JEL codes: C21; C33; E31; Q54.
Keywords: Climate Change; Food price inflation; Panel data; Quantile regression;

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1 Introduction

As articulated in the most recent publication by the Intergovernmental Panel on Climate Change, it has become undeniably clear that anthropogenic factors are the primary drivers of greenhouse gas emissions, which have decisively contributed to global warming.[1] This phenomenon is evidenced by the observed increase in global surface temperature, which has risen by 1.1°C above pre-industrial levels (1850–1900) during the period 2011–2020. Projections related to climate change indicate a potential escalation in global mean temperature by up to 4°C over the forthcoming century. This trend is anticipated to exert profound impacts on various economic indicators.

Climate change is getting increased attention not only within the academic and business arena across various disciplines but also among central banks, with explicit mandates for price stability. This heightened focus stems from the impact of climate change on their capacity to maintain price stability. As the repercussions of climate change become progressively more pronounced, comprehending its implications has become very important. Extensive research has been undertaken to assess the influence of climate variables, particularly temperature and precipitation fluctuations, on numerous economic and agricultural dimensions. These include GDP growth as well as crop yields, agricultural output, and the pricing dynamics of agricultural and food products.

A growing literature on climate-economic activity nexus unanimously suggests a negative relationship between higher temperature and economic output.[2] This relationship is clarified through the application of diverse methodologies, climate data, and clustering techniques, which include the incorporation of various dummy variables and their interactions, as well as non-linearity within the models. Such analyses reveal heterogeneous effects of climate change, underscoring the complex dynamics at play. Research has demonstrated that the economic impacts of climate change tend to be more severe in low-income and developing countries. For instance, Dell et al. (2012) found significant adverse effects of higher temperatures on economic performance in poorer countries. Similarly, Kalkuhl and Wenz (2020) highlighted the heightened vulnerability of low-income countries to climatic shifts, and Cevik and Jalles (2023) provided further evidence of the disproportionate economic burden borne by these nations. Additionally, Ciccarelli and Marotta (2024) reinforced these findings, emphasising the critical need for nuanced policy interventions tailored to mitigate the specific challenges faced by economically disadvantaged countries.

While there is broad consensus on the interplay between climate change and economic activity, there remains a lack of clarity regarding its inflationary effects. The impact on prices is complex and sometimes contradictory.[3] As articulated by Natoli (2023), this ambiguity may arise from the significant influence of temperature changes

[1] See Lee et al. (2023) for details.

[2] See Dell et al. (2012), Burke et al. (2015), Colacito et al. (2019), Felbermayr and Gröschl (2014), Acevedo et al. (2020), Cevik and Jalles (2023), Kolstad and Moore (2020), Ciccarelli and Marotta (2024) and Kim et al. (2021).

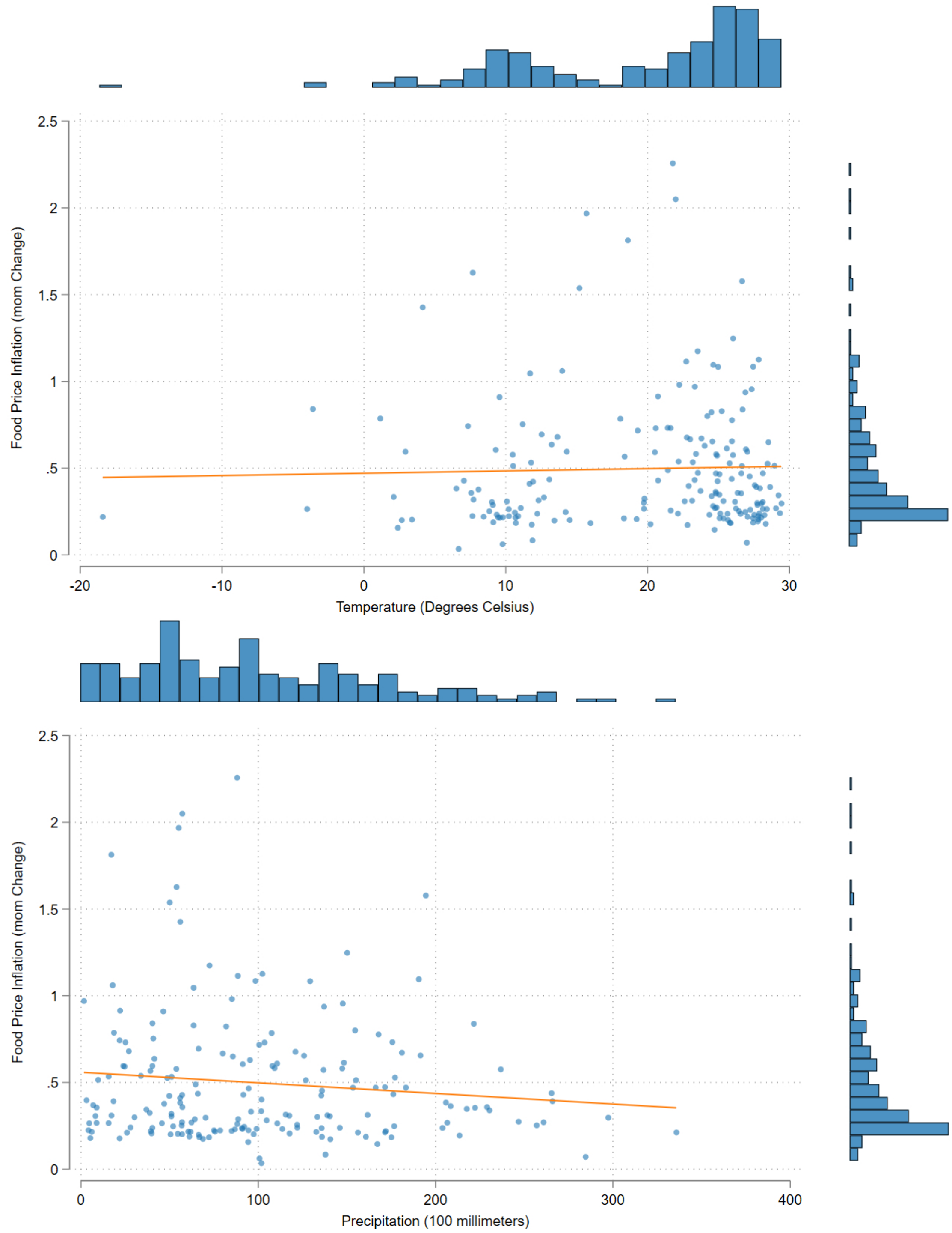
[3] See Mukherjee and Ouattara (2021), Faccia et al. (2021) and Natoli (2023).

on both the demand and supply sides of the economy. On the supply side, extreme temperatures can disrupt agricultural yields and industrial productivity, potentially leading to higher prices. Conversely, on the demand side, temperature variations can alter energy consumption patterns, such as reduced heating needs in warmer winters or increased cooling demands in hotter summers, which can influence energy prices in opposing directions. These opposing forces can offset each other, making it difficult to predict the overall effect on inflation over different time horizons. Therefore, the net impact of climate change on inflation remains an intricate subject requiring further empirical investigation and meticulous understanding.

This study contributes to the relatively underexplored literature on the inflationary consequences of climate change. Early research, such as that by Parker (2018) and Heinen et al. (2019), primarily investigates the impact of natural hazards on consumer price inflation, with a focus on sub-components such as food, housing, and energy. Faccia et al. (2021) find that extreme temperatures, particularly those occurring during summer, have a long-lasting impact on inflation, primarily through food prices, a phenomenon that is particularly evident in emerging economies. Similarly, Lucidi et al. (2024) demonstrate that high spring-summer temperatures increase headline inflation in major eurozone countries. Mukherjee and Ouattara (2021) provide compelling evidence on the significance of temperature shocks on inflation in developing countries, noting that the effects of such shocks can persist for several years, thereby posing substantial risks to monetary policy.

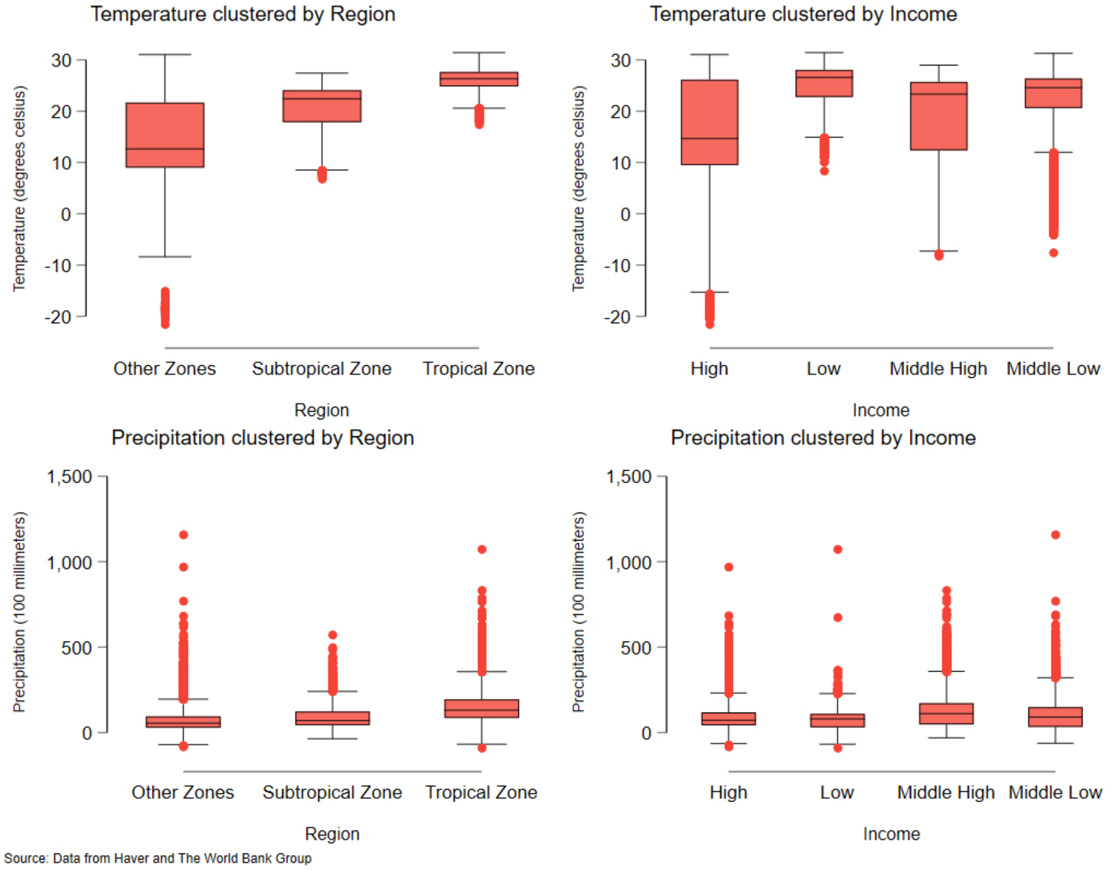
According to Kabundi et al. (2022), the inflationary impact of temperature shocks is contingent on the type and intensity of the shocks, the income level of the country, and the prevailing monetary policy regimes. In a recent paper, Ciccarelli et al. (2023) highlight significant country-specific asymmetries and seasonal responses of inflation to temperature shocks, which primarily affect food, energy, and service prices. Kotz et al. (2024) employ fixed-effects regressions on over 27,000 observations of monthly consumer price indices to quantify the impacts of climate conditions on inflation. Their findings reveal that higher temperatures lead to persistent increases in both food and headline inflation over 12 months in both high and low-income countries. This heterogeneity in the impact of temperature change on inflation is further supported by the work of Cevik and Jalles (2023). Their findings underscore the varying effects across different economic contexts.

Figure 1: Food price inflation, temperature and precipitation



In this study, we investigate the impact of temperature and precipitation on food price inflation, contributing to the academic literature with two critical research questions. First, does the association between weather variables and food price inflation vary when food inflation is at its upper or lower extremes? Second, does this association differ more significantly due to a country's geographic location rather than its income level or the size of its agricultural sector?

Figure 2: Temperature and precipitation by different income levels and regions



We assess these two research questions using a dataset, which consists of monthly observations for 186 countries from 2000 to 2022. Figure 1 shows a scatterplot-histogram and a linear fit of the relevant variables that we studied in this paper. The Food and Agriculture Organization of the United Nations (FAO) provides country-level food price inflation data at a monthly frequency. Although the use of monthly data has certain constraints, it facilitates the analysis of 51,150 observations in total, allowing for a comprehensive examination of the dynamics between climate change and food price inflation and the heterogeneity of these effects across different regions and countries. Existing scholarly literature, including studies by Colacito et al. (2019) and Faccia et al. (2021), indicates that the impact of climatic factors on macroeconomic variables intensifies with higher data frequency. By employing monthly data, this research aims to offer a detailed understanding of the intricate relationship between climatic changes and food price inflation. Figure 2 illustrates the temperature and precipitation averaged over 2000-2022 by region and income. We can easily observe the differences between temperatures and precipitation between tropical regions and non-tropical regions.

Our empirical framework quantifies the plausible effects of weather variables using fixed-effects panel regression models, exploiting within-country variation. Country-fixed effects account for unobserved differences between countries, while the use of year-fixed effects accounts for contemporaneous common shocks. We adjust weather variables and the food price index series for seasonality before including it in the analysis to account for country-specific seasonality. Our study does more than just focus on the median or mean effects, which are commonly addressed in existing literature. We direct our attention towards the upper and lower quantiles under the premise that tail events may become more frequent in the context of a delayed transition to a net-zero economy. This aspect of our research provides new insights into the potential intensification of extreme outcomes under varying climate scenarios, thereby contributing to a more nuanced understanding of the broader economic implications of climate change. While ordinary regression analysis estimates the conditional expectation of the mean, quantile regression makes it possible to examine the shape of the entire distribution through the estimation of quantile points. Such an approach is particularly insightful as it enables us to discern both the impact of extreme climate events on food price dynamics and its implications on food price inflation at the extreme ends of the spectrum.

Through our analysis, we have obtained several significant results. First, feedback effects are crucial, and ignoring them may lead to misleading conclusions. When analysing a large number of countries and high-frequency data, it is essential to account for lagged inflation. Second, our estimates indicate that higher temperatures initially reduce food inflation significantly. However, the cumulative effect is inflationary after a year. We also find that at the higher percentiles of inflation, the immediate response to temperature change is relatively larger and more significant. Yet, the cumulative effects are nearly identical across quantiles. Third, when we cluster the countries with respect to their income level, our overall regression analyses do not suggest any significant differential temperature effect between high-income and low-income countries. Lastly, unless inflation is decomposed into its quantiles, we find no difference in the response of inflation to temperature changes between agricultural and non-agricultural countries. However, evidence indicates that when inflation is in the upper quantile for an agricultural country, food price inflation tends to decrease significantly in response to a rise in temperature.

Regarding precipitation, our results suggest a relatively small association between precipitation and food price inflation. Although small, the overall impact is significant and positive. When interaction dummies for income and agriculture are included, the effect of precipitation on food price inflation is significantly negative for low-income countries but positive for agricultural countries. Quantile regression analysis provides evidence of the differential effects of precipitation on lower and upper quantiles. In low-income countries, an increase in precipitation has an inflationary impact when inflation is low and a deflationary impact when inflation is high. Conversely, the opposite relationship is observed for agricultural countries, i.e., an increase in precipitation has a deflationary impact when inflation is low and an inflationary impact when inflation is high. This means that if a low-income country is already struggling with high levels of food price inflation, a precipitation increase will make things worse. This result has very important implications for low-income countries as these countries have a higher share of food prices in their consumer basket.

This paper is organised as follows. Section 2 presents the details of the data and dummy variables we used for this study. Section 3 describes the methodology used in the analysis. Section 3.1 describes our baseline panel regression with fixed effects, and section 3.2 demonstrates how we extend our baseline results to different quantiles of food price inflation. Section 4 discusses our key results. Section 5 provides robustness checks and additional findings, and section 6 concludes.

2 Data

Climate Data

The country-level monthly mean surface temperature and precipitation are taken from HAVER Analytics. The data set is consistent with those in the World Bank Climate Change Knowledge Portal (CCKP).[4] CCKP historical data originates from observational datasets and allows users to understand past and current climate contexts. Observed, historical climate data is generated from thousands of weather stations worldwide, which collect temperature and rainfall data in a continuous manner or from satellites. Observed data presents mean, minimum and maximum temperatures and precipitation. Observational data is sourced from the Climatic Research Unit (CRU) of the University of East Anglia. CRU provides gridded historical datasets derived from observational data and quality-controlled temperature and rainfall data, as well as derivative products such as monthly and long-term historical climatologies. CRU data is widely accepted as a reference dataset in climate research.[5] Observed data is presented at a spatial resolution, 0.5° x 0.5° (50km x 50km). Monthly mean surface temperature and precipitation are restricted to December 2022, and that is the reason why our analysis is restricted to that period. The descriptive statistics of climate data at the country level are illustrated in the Appendix.[6]

Dummy variables

Regional dummy

We classified countries according to whether they are tropical or not. We used the World Population Review 'Tropical Countries 2024' classification to come up with our regional dummy variable.[7] Tropical countries are located in the belt-shaped region of

[4] See WorldBank (2021) for details.
[5] See Alessandri and Mumtaz (2023) for details.
[6] See Table A1 and A2.
[7] Data source is available in https://worldpopulationreview.com/country-rankings/tropical-countries

the Earth closest to the Equator, horizontally bordered by the Tropic of Cancer (23°) to the north and the Tropic of Capricorn (23°) to the south. These countries make up about 40% of the planet's surface area and host about 40% of the world's population. Tropical countries tend to have hotter, wetter, more humid weather than countries located in the middle latitudes/temperate regions and the polar regions. Most tropical countries have average monthly temperatures of 18°C (64.4°F) or higher, and the year consists of two seasons: the wet/rainy and the dry season. Subtropical countries are geographical and climate zones to the north and south of the tropics. Geographically, part of the temperate zones of both hemispheres cover the middle latitudes from 23°26' to about 35° north and south. According to the 2024 World Population Review report, Argentina, Chile, China, Egypt, and the United States are classified within the subtropical region. Conversely, North Korea, South Korea, Morocco, Bhutan, Nepal, and Tunisia are not categorised as tropical regions. For our study, we adhere to this classification system to assign countries to their respective climatic regions.

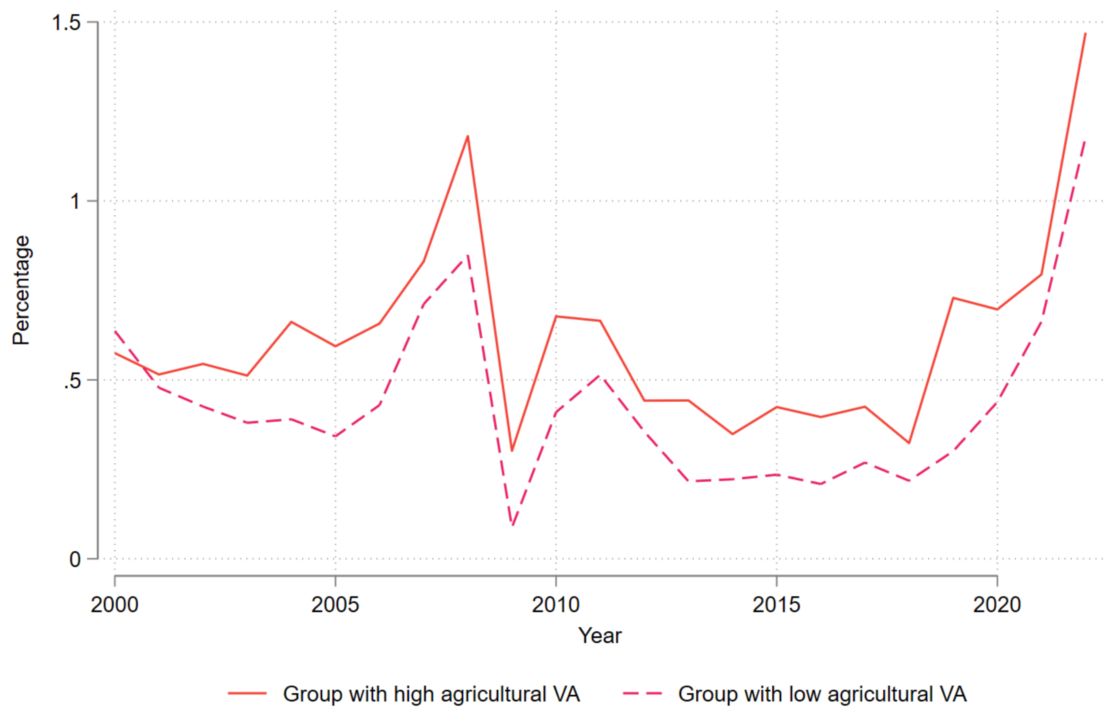
Income dummy

The income dummy is constructed using the World Bank income classification for 2022. Hence, countries are classified into four groups. Low-income countries are those with a gross national income (GNI) per capita of 1,135 US dollars or less; Lower-middle-income countries are those with a GNI per capita between 1,136 and 4,465 US dollars; Upper-middle-income countries are those with a GNI per capita between 4,466 and 13,845 US dollars; High-income countries are those with a GNI per capita of 13,846 US dollar or more. Four different income dummies are defined for each income level, and the dummy variable takes one if the country is in the relevant income group.

Agricultural dummy

To compute the agricultural country dummy, we first obtained the data on the share of agricultural value added in GDP for the period 2000-2022 from the World Bank. Then, we calculated the period average for each country. The agricultural country dummy variable takes the value of 1 if the country average is above the overall mean and zero if it is below.

Figure 3: Monthly food price inflation in agricultural and non-agricultural countries



Food price inflation

For this study, we employ the FAO monthly food price index statistics spanning from January 2000 to December 2022. This dataset includes national-level food price data for 203 countries. Despite the relatively brief time span, the extensive coverage of countries facilitates a more enriched cross-country analysis. Due to the absence of monthly data for Australia and significant data gaps or fluctuations in several island nations, these countries were excluded from our final dataset. Consequently, our analysis encompasses 186 countries, enabling us to account for cross-country heterogeneity effectively. While alternative cross-country food price indices, such as those developed by Ha et al. (2023), are available, they cover a significantly smaller number of countries compared to the FAO dataset. Hence, the FAO dataset offers a more comprehensive and reliable foundation for our comparative analysis, enhancing the robustness and validity of our findings by leveraging a broader and more detailed dataset. Figure 3 presents the aggregated food price inflation data for countries with high agricultural value added and those with low agricultural value added. The disparity in food price inflation between these two groups is clearly visible, and we will explore this difference in greater detail in subsequent sections, particularly in the context of clustering analysis.

Prior to conducting the regression analysis, both the food price data and the temperature and precipitation data were deseasonalised using the TRAMO-SEATS procedures. This methodological approach ensures that the seasonal effects are removed, providing a clearer picture of the underlying trends. In alignment with the methodology employed by Kotz et al. (2024), our benchmark regression analysis utilises month-on-month inflation rates as the primary dependent variable. These rates are calculated as the first difference in the logarithm of the food price index. This approach allows for a more precise estimation of the dynamic relationship between food prices and the climatic variables under consideration. The descriptive statistics of food price inflation at the country level are illustrated in the Appendix.[8]

3 Empirical Methodology

In this section, we develop the empirical framework for analysing the impact of temperature and precipitation on food price inflation. Our panel regression analysis adjusts standard errors for clustering at the regional level based on the hypothesis that a country's sensitivity to climate change is predominantly influenced by its latitudinal characteristics rather than its income level. The regional dummy variable is defined according to the classification provided by the World Population Review classification.[9] Figure 1 clearly demonstrates that clustering becomes evident when the latitudinal characteristics of countries are taken into account. To ensure the robustness of our results, we also adjust standard errors for clustering at the income level. Furthermore, we present our results without clustering adjustments to offer a comprehensive analysis.

Our analytical framework addresses autocorrelation by incorporating lagged values of inflation, thereby controlling for feedback effects. Furthermore, we employ a highly flexible model by including lagged variables for both temperature and precipitation. This allows us to investigate both the immediate and cumulative impacts of these climatic factors on food price inflation. By testing the immediate and cumulative effects of climate change, our approach makes a significant contribution to the existing literature. Moreover, it explores how these effects manifest across different levels of inflation extremes. This comprehensive methodology provides a nuanced understanding of the temporal dynamics and variability in the relationship between climate variables and inflation, enhancing the robustness and depth of our empirical findings.

3.1 Panel fixed effect model

We consider three panel fixed effect regressions. Our empirical analysis is similar to Dell et al. (2012), yet our dependent variable and research question are different. We also use intra-annual frequency for all our empirical estimations. In our first panel fixed effects specification, inflation is modelled as:

$$INF_{i,t} = \alpha_i + \gamma_t + \beta_s X_{s,i,t} + \varepsilon_{i,t} \tag{1}$$

[8] See Table A3.

[9] Source: https://worldpopulationreview.com/country-rankings/tropical-countries

where $INF_{i,t}$ is the food price inflation for country i at time t. $X_{s,i,t}$ is monthly average of s, where s is a matrix composed of temperature and precipitation. α_i, for $i = 1...N$ capture the country i fixed effects and γ_t, for $t = 1...T$ are time fixed effects. β_s is the slope coefficient to be estimated for each s, showing the impacts of climate shocks on food price inflation. $\varepsilon_{i,t}$ is an error term clustered simultaneously by region.

In our second panel fixed effects specification, we extend the basic model above to control for auto-correlation by adding up to 12-period lagged inflation. Therefore, inflation is modelled as:

$$INF_{i,t} = \alpha_i + \gamma_t + \beta_s X_{s,i,t} + \sum_{k=0}^{12} \phi_k INF_{i,t-k} + \varepsilon_{i,t} \tag{2}$$

where ϕ_k is the vector of unknown parameters to be estimated and shows the relationship between current inflation and its lags. The size and significance of ϕ_k provide information about the inflationary feedback.

According to Dell et al. (2012) and Colacito et al. (2019), distinguishing between the immediate and cumulative effects of climate shocks is essential because the effects on the macroeconomic variable (in our case, inflation) accumulate over time and may become more quantitatively important than the immediate effects. Therefore, in our third panel fixed effects specification, we account for the immediate and cumulative effects of climate shocks by adding lags of temperature and precipitation to our model.

$$INF_{i,t} = \alpha_i + \gamma_t + \sum_{j=0}^{L} \beta_{s,j} X_{s,i,t-j} + \sum_{k=0}^{12} \phi_k INF_{i,t-k} + \varepsilon_{i,t} \tag{3}$$

where $\beta_{s,j}$ are unknown slope parameters to be estimated for $j = 0...L$ lagged climate related variables.

When $\beta_{s,j} = 0$ and $\beta_s = 0$, then there is no temperature or precipitation impact on food price inflation. In the model with lags, we separately test the immediate, $\beta_{s,0} = 0$, and accumulated, $\sum_{j=0}^{L} \beta_{s,j} = 0$, effects of each climate shocks from s.

3.2 Quantile regression model

Our quantile panel regression model is based on the work of Machado and Silva (2019).[10] Machado and Silva (2019) builds on the quantile regression literature and study the conditions under which it is possible to estimate regression quantiles by estimating conditional means. They propose a method for estimating conditional quantiles by combining estimates of the location and scale functions, which are obtained from the conditional expectations of appropriately defined variables. Their method has the advantage of allowing the use of techniques applicable solely to conditional means, such as differencing out individual effects in panel data models, while also offering insights into how

[10] Koenker and Bassett Jr (1978), Koenker and Hallock (2001) and Koenker (2005) are authoritative references in the quantile regression analysis. See also Gutenbrunner and Jurecková (1992), He (1997), Zhao (2000)

regressors impact the entire conditional distribution. Additionally, their approach ensures that the estimated regression quantiles do not cross.

Based on the work of Machado and Silva (2019), we consider the estimation of the conditional quantiles $Q_{INF}(\tau|X_{s,i,t})$ for a location-scale model of the form:

$$INF_{i,t} = \alpha_i + \gamma_t + \beta_s X_{s,i,t} + (\delta_i + Z'_{i,t}\lambda)\varepsilon_{i,t} \tag{4}$$

with $Pr\{\delta_i + Z'_{i,t}\lambda > 0\} = 1$ The parameters α_i and δ_i capture the individual fixed effects. The sequence $X_{s,i,t}$ is strictly exogenous, i.i.d. for any fixed i, and independent across i. $\varepsilon_{i,t}$ are i.i.d. (across i and t), statistically independent of $X_{s,i,t}$, and normalized to satisfy the moment conditions $E(\varepsilon) = 0$ and $E(|\varepsilon|) = 1$.

The model above implies that:

$$Q_{INF}(\tau|X_{s,i,t}) = (\alpha_i + \delta_i q(\tau)) + X'_{s,i,t}\beta_s + Z'_{i,t}\lambda q(\tau) \tag{5}$$

The scalar coefficient $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ represents the quantile-τ or the distributional fixed effect for individual i at τ. The distributional effect represents the effect of time-invariant individual characteristics which, like other variables, are allowed to have different impacts on different regions of the conditional distribution of $INF_{i,t}$. α_i, then, can be interpreted as the average effect for individual i, due to the fact that $\int_0^1 q(\tau)\, d\tau = 0$. The model is estimated using the method of moments quantile regression method.[11]

The general procedures followed in the estimation of (5) are summarised as follows:

Step 1: Regress $(INF_{i,t} - \sum INF_{i,t}/T)$ on $(X_{s,i,t} - \sum X_{s,i,t}/T)$ by OLS to attain $\hat{\beta}_s$;

Step 2: Estimate $\hat{\alpha}_i = 1/T \sum (INF_{i,t} - X'_{s,i,t}\hat{\beta}_s)$ and obtain A the residuals $\widehat{\epsilon_{i,t}} = INF_{i,t} - X'_{s,i,t}\hat{\beta}_s$;

Step 3: Regress $|\widehat{\epsilon_{i,t}}| - \sum |\widehat{\epsilon_{i,t}}|/T$ on $Z_{i,t} - \sum Z_{i,t}/T$ to attain $\hat{\lambda}$;

Step 4: Estimate $\hat{\delta}_i = 1/T \sum (|\widehat{\epsilon_{i,t}}| - Z'_{i,t}\hat{\lambda})$;

Step 5: Estimate q_τ by $\hat{q}$, solution to $\min_q \sum_i \sum_t \rho_\tau(\widehat{\epsilon_{i,t}} - (\hat{\delta}_i + Z'_{it}\hat{\lambda})q)$;

where $q_\tau(A) = (\tau - 1)AI\{A \leq 0\} + \tau AI\{A > 0\}$ is the check-function.

A general form of the quantile regression with lags and auto-correlation components can be written as follows:

$$Q_{INF}(\tau|X_{s,i,t}) = (\alpha_i + \delta_i q(\tau)) + \sum_{j=0}^{L} \beta_{s,j} X_{s,i,t-j} + \sum_{k=0}^{12} \phi_k INF_{i,t-k} + Z'_{i,t}\lambda q(\tau) \tag{6}$$

Then, similar procedures above can be followed to test the significance of the immediate and cumulative effects of climate shocks on food price inflation.

[11] The Stata procedure *mmqreg* provided by Santos Silva was used to obtain the method of moments quantile regression estimates.

4 Results

4.1 Baseline regression results

Table 1 evaluates the null hypothesis that temperature and precipitation do not affect food price inflation. Models represented by Table 1 do not incorporate lagged variables or terms for autocorrelation. To assess the potential for a non-linear relationship between weather variables and food price inflation, the squared terms of temperature and precipitation are included. The table presents results from both panel fixed effects models and quantile regression analyses. Specifically, four distinct models are examined. The first model (Model 1 column of Table 1, **FE**) employs robust standard errors within a linear framework, while the second model (Model 2 column of Table 1, **FE_clus**) adjusts standard errors for regional clustering. The third and fourth models (**FE_NL** and **FE_NL_clus**) represent the non-linear counterparts of the first and second models, respectively, incorporating the squared terms of the climatic variables. By comparing these models, we aim to discern the linear and non-linear impacts of temperature and precipitation on food price inflation, providing a comprehensive analysis of these effects under different statistical assumptions.

In classifying regions, we categorise countries into three groups: tropical, subtropical, and others. This grouping deviates from traditional classifications in the literature. However, we posit that a country's latitudinal location holds greater significance than conventional geographical classifications when examining the relationship between climate change and economic variables, specifically food prices.

The first column of Table 1 reveals a significant negative relationship between temperature and food price inflation, on average, across all countries. This negative relationship is plausible since the dependent variable is month-to-month inflation. Discrepancies can occur when harvesting periods, temperature increases, and inflation realisations do not coincide, leading to unexpected results in the current period. Ciccarelli et al. (2023) examine the seasonal impact of temperature on food inflation, distinguishing between processed and unprocessed foods, and confirm the lagged and heterogeneous effects of temperature changes across different seasons. In the subsequent section, we explore the cumulative effects of temperature, although our data do not allow for a detailed distinction between processed and unprocessed foods. The estimated coefficient for precipitation is also significant but positive. Column 2 shows no significant change in the estimated coefficients when robust standard errors are adjusted for clustering at the regional level. Additionally, Columns 2 and 3 do not provide evidence supporting nonlinear effects, as the respective estimated coefficients are statistically insignificant. Consequently, the panel fixed effect models suggest that, on average, a 1°C increase in temperature decreases food price inflation by 0.04 percentage points. In comparison, a 1 unit (100 mm) increase in precipitation increases food price inflation by 0.0003 percentage points.

Table 1: Baseline panel regressions (Cluster=region)

Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus	(Model 5) FE_q10	(Model 6) FE_clus_q10	(Model 7) FE_NL_q10	(Model 8) FE_NL_clus_q10	(Model 9) FE_q90	(Model 10) FE_clus_q90	(Model 11) FE_NL_q90	(Model 12) FE_NL_clus_q90
Temperature	-0.0369***	-0.0369***	-0.0286**	-0.0286**	-0.0255***	-0.0255**	-0.0299***	-0.0299**	-0.0499***	-0.0499***	-0.0271	-0.0271***
	(0.0074)	(0.0114)	(0.0141)	(0.0122)	(0.0072)	(0.0104)	(0.0114)	(0.0121)	(0.0110)	(0.0131)	(0.0174)	(0.0099)
Precipitation	0.0003**	0.0003***	0.0005**	0.0005	0.0002	0.0002***	0.0005	0.0005	0.0003	0.0003*	0.0006	0.0006**
	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0003)	(0.0004)	(0.0003)	(0.0002)	(0.0005)	(0.0003)
Temperature^2			-0.0003	-0.0003			0.0002	0.0002			-0.0010	-0.0010
			(0.0005)	(0.0011)			(0.0005)	(0.0009)			(0.0007)	(0.0008)
Precipitation^2			-0.0000	-0.0000			-0.0000	-0.0000			-0.0000	-0.0000***
			(0.0000)	(0.0000)			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Constant	1.2860***	1.2860***	1.2297***	1.2297***	-1.2234***	-1.2234***	-1.2057***	-1.2057***	4.1480***	4.1480***	4.0055***	4.0055***
	(0.1181)	(0.0898)	(0.1449)	(0.0244)	(0.2003)	(0.1838)	(0.2029)	(0.0722)	(0.3071)	(0.0915)	(0.3107)	(0.1019)
Observations	51,150	51,150	51,150	51,150	51,150	51,150	51,150	51,150	51,150	51,150	51,150	51,150
Number of cross sections	186	186	186	186								

Notes: All specifications include country and year fixed effects. All models, including the term ”clus” have robust standard errors in parenthesis adjusted for clustering at the regional level. 186 countries are divided into 3 different regional statuses, i.e., tropical, subtropical and the remaining countries. Temperature is in degrees Celsius, and precipitation is in units of 100 mm.
Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Next, we evaluate the changing impact of climate variables on food price inflation in different ranges of food price inflation. Model 5 to Model 12 of Table 1 focuses on this particular evaluation, reporting the results from the quantile regression analyses for the events at tails, namely lower (q=0.10) and upper (q=0.90) quantiles of food price inflation. Columns 5-8 report the regression results for the lower quantile, where food price inflation is relatively low. These columns elucidate how temperature and precipitation influence food price inflation when it is in the lower decile of the distribution. In contrast, columns 9-12 provide the regression results for the upper quantile, where food price inflation is relatively high. This allows us to explore the effects of climate variables when food price inflation is in the upper decile of the distribution.

The comparison of columns 5 and 9 (Model 5 and 9) reveals that the estimated coefficients for temperature are both negative and significant across the lower and upper quantiles. Notably, the impact of temperature on food price inflation in the upper quantile is precisely double that observed in the lower quantile. This indicates a substantially stronger relationship between temperature shocks and food price inflation in countries experiencing high food price inflation. This conclusion remains valid even when using clustered robust errors.

Additionally, the statistical significance of the precipitation effect appears sensitive to model specification. The relationship between precipitation and food price inflation intensifies when standard errors are adjusted for clustering at the regional level. Specifically, an additional 100 mm of monthly precipitation is associated with a 0.0002 percentage point increase in food price inflation in the lower quantile. In contrast, it contributes an additional 0.0001 percentage points in the upper quantile. This result is expected, given the fact that tropical regions have much higher precipitation levels compared to other regions.

However, it is important to note that the estimation results for the upper quantile are particularly sensitive to non-linearity, indicating that these findings should be interpreted with caution. This sensitivity underscores the complexity of the relationship between climatic variables and food price inflation, necessitating careful consideration of model specifications.

Figure 4 plots the estimated coefficients for temperature and precipitation over the different quantiles of food price inflation. It shows that the impact of temperature on inflation increases with the increase in inflation level. The effect varies between -0.02 and -0.05 as the inflation quantile increases from 10 to 90. Figure 4 also illustrates that the change in the coefficient of precipitation over different quantiles is much smaller yet significant.

4.2 Model with lagged dependent variables

Our baseline model, with no lags of the dependent and independent variables, provided supporting evidence not only on the link between food price inflation and climate

Table 2: Baseline panel regressions with 12 lags of inflation (Cluster=region)

Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus	(Model 5) FE_q10	(Model 6) FE_clus_q10	(Model 7) FE_NL_q10	(Model 8) FE_NL_clus_q10	(Model 9) FE_q90	(Model 10) FE_clus_q90	(Model 11) FE_NL_q90	(Model 12) FE_NL_clus_q90
Temperature	-0.0393***	-0.0393***	-0.0317**	-0.0317*	-0.0247	-0.0247**	-0.0239	-0.0239*	-0.0544	-0.0544***	-0.0398	-0.0398***
	(0.0066)	(0.0094)	(0.0125)	(0.0169)	(0.0284)	(0.0110)	(0.0832)	(0.0142)	(0.0520)	(0.0089)	(0.0860)	(0.0137)
Precipitation	0.0003**	0.0003***	0.0005**	0.0005***	0.0002	0.0002**	0.0004	0.0004	0.0004	0.0004***	0.0006	0.0006*
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0007)	(0.0001)	(0.0023)	(0.0005)	(0.0012)	(0.0001)	(0.0024)	(0.0003)
Temperature^2			-0.0003	-0.0003			-0.0000	-0.0000			-0.0006	-0.0006
			(0.0004)	(0.0012)			(0.0035)	(0.0011)			(0.0036)	(0.0008)
Precipitation^2			-0.0000	-0.0000***			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Constant	0.7330***	0.7330***	0.6842***	0.6842***	-1.1261	-1.1261***	-1.1380	-1.1380***	2.6592*	2.6592***	2.5748*	2.5748***
	(0.1082)	(0.1260)	(0.1211)	(0.0300)	(0.7998)	(0.1907)	(1.4499)	(0.0829)	(1.4643)	(0.0712)	(1.4993)	(0.0752)
Observations	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918
Number of cross sections	186	186	186	186								

Notes: All specifications include country and year fixed effects. All models, including the term "clus" have robust standard errors in parenthesis adjusted for clustering at the regional level. 186 countries are divided into 3 different regional statuses, i.e., tropical, subtropical and the remaining countries. Temperature is in degrees Celsius, and precipitation is in units of 100 mm.

Robust standard errors in parentheses

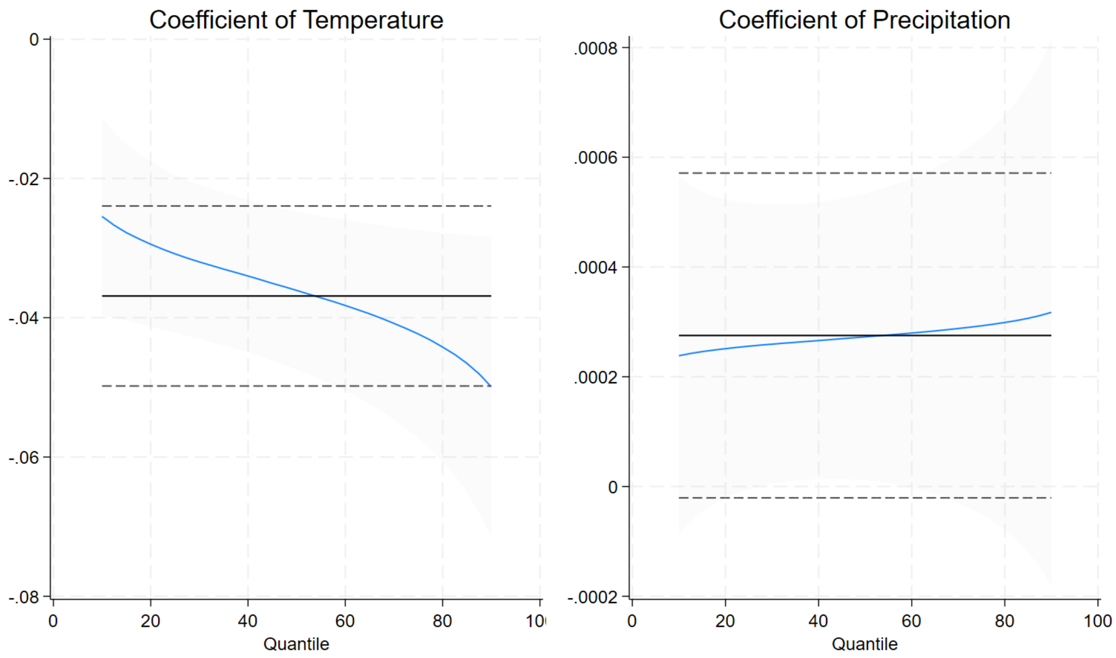
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Baseline panel regressions with 1^{st} and 12^{th} lag of inflation (Cluster=region)

Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus	(Model 5) FE_q10	(Model 6) FE_clus_q10	(Model 7) FE_NL_q10	(Model 8) FE_NL_clus_q10	(Model 9) FE_q90	(Model 10) FE_clus_q90	(Model 11) FE_NL_q90	(Model 12) FE_NL_clus_q90
Temperature	-0.0378***	-0.0378***	-0.0269**	-0.0269**	-0.0259	-0.0259**	-0.0252	-0.0252*	-0.0506	-0.0506***	-0.0287	-0.0287***
	(0.0067)	(0.0091)	(0.0126)	(0.0127)	(0.0320)	(0.0109)	(0.0673)	(0.0139)	(0.0314)	(0.0100)	(0.0630)	(0.0076)
Precipitation	0.0003**	0.0003***	0.0005**	0.0005***	0.0003	0.0003***	0.0005	0.0005	0.0003	0.0003**	0.0006	0.0006*
	(0.0001)	(0.0000)	(0.0002)	(0.0002)	(0.0008)	(0.0001)	(0.0019)	(0.0005)	(0.0008)	(0.0001)	(0.0018)	(0.0003)
Temperature^2			-0.0005	-0.0005			-0.0000	-0.0000			-0.0009	-0.0009
			(0.0004)	(0.0010)			(0.0028)	(0.0011)			(0.0027)	(0.0006)
Precipitation^2			-0.0000	-0.0000***			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Food inflation (t-1)	0.2278***	0.2278***	0.2278***	0.2278***	0.0323	0.0323	0.0322	0.0322	0.4365***	0.4365***	0.4365***	0.4365***
	(0.0693)	(0.0818)	(0.0693)	(0.0817)	(0.0981)	(0.0272)	(0.1278)	(0.0268)	(0.0962)	(0.1163)	(0.1198)	(0.1164)
Food inflation (t-12)	0.0603*	0.0603	0.0604*	0.0604	0.0032	0.0032	0.0032	0.0032	0.1213*	0.1213**	0.1214	0.1214**
	(0.0319)	(0.0391)	(0.0319)	(0.0391)	(0.0659)	(0.0086)	(0.0859)	(0.0085)	(0.0646)	(0.0580)	(0.0805)	(0.0581)
Constant	0.9328***	0.9328***	0.8634***	0.8634***	-1.0259	-1.0259***	-1.0387	-1.0387***	3.0229***	3.0229***	2.8935***	2.8935***
	(0.1081)	(0.1023)	(0.1233)	(0.0429)	(0.8669)	(0.1781)	(1.1409)	(0.0681)	(0.8496)	(0.0588)	(1.0693)	(0.0645)
Observations	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918
Number of cross sections	186	186	186	186								

Notes: All specifications include country and year fixed effects. All models, including the term ”clus” have robust standard errors in parenthesis adjusted for clustering at the regional level. 186 countries are divided into 3 different regional statuses, i.e., tropical, subtropical and the remaining countries. Temperature is in degrees Celsius, and precipitation is in units of 100 mm.
Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 4: Quantile Plot (Table 1-Model 5)



variables but, more importantly, differentiating the impact between high and low food price inflation events. In this section, we include up to 12 lags of food price inflation in regression analysis to control for the possible influence of auto-correlation on the dynamics of the temperature and precipitation effects. None of the models include lags of temperature or precipitation yet.

Table 2 illustrates that the point estimates of temperature for Model 1 and Model 2 remain negative, and there appears to be a slight increase in their size. The estimated parameters remain negative and stable even after accounting for non-linearity. When we consider the quantile regressions, results are negative and stable if standard errors are adjusted for clustering at the region. The estimated coefficients of temperature and precipitation for the upper tail are relatively larger than those for the lower tail. To save space, we do not include the lags of inflation in Table 2.

Table 3 shows that there is no significant change in the results even if we keep only the first and 12th-month lags of food price inflation in the regression analyses. Table 3 also points out that current inflation is positively and significantly related to the previous month's inflation. The relationship is statistically strong, showing that a one percentage increase in inflation increases current-period inflation by about 0.23 percentage points for the entire sample. The feedback effect is approximately twice as large for the upper quantile, while it is statistically insignificant for the lower quantile.

4.3 Model with lags of temperature and precipitation

In this section, we consider more flexible models and add 12 lags of both temperature and precipitation to our regression analysis. By doing this, we aim to account for both immediate and cumulative effects of climate changes described in Section 3 to assess better the dynamics of the relationship between temperature as well as precipitation and food price inflation.

Regression results, including temperature lags, are summarised in Table 4. Those, including precipitation lags, are reported in the section where we discuss robustness checks. The bottom row of each column of Table 4 reports cumulative effects calculated by summing the coefficients of the respective temperature variables and their lags.

The estimated coefficients for temperature and precipitation remain stable after the addition of temperature lags. There is no change in feedback effects either, except that if standard error is not adjusted for clustering, the coefficient for the upper quantile becomes insignificant. In addition, the cumulative and immediate effects of temperature have opposite signs. Table 4 shows that the cumulative effects of temperature are positive and statistically significant at one percentage level. Temperature shock may reduce food inflation due to level effects, but once temperature shock disappears, level effects are expected to reverse. The coefficient of the lags of temperature does not sum up to zero and, in fact, is significantly positive, suggesting that the impact of temperature persists over a year and is inflationary. Food price inflation gradually adjusts to temperature shock.

Statistical significance and size of the coefficients do not vary between upper and lower quantiles. A 1° C temperature rise produces about 0.051 percentage point increase in monthly food price inflation. However, quantile regressions suggest that clustering is a decisive factor in determining the statistical significance of this cumulative effect.

Moreover, the size of the cumulative effect is larger than the absolute size of the immediate effect, and this difference is larger for the lower quartile. These outcomes are primarily important and imply that food price inflation adjusts gradually with rising temperatures. The adjustment process is higher if inflation fluctuates at lower rates.

4.4 Model with lags of temperature, precipitation and interaction dummies

The previous sections confirm that the immediate and cumulative effects of temperature are significant factors in determining food price inflation. It also underlies the significance of clustering in such an analysis. This section considers extending the models above to examine if income differences, as well as the size of the agricultural sector, play important roles in determining the magnitude and significance of temperature effects. The majority of cross-country papers published within the framework of

Table 4: Baseline panel regressions with 1^{st} and 12^{th} lag of inflation and cumulative effect of temperature (Cluster=region)

Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus	(Model 5) FE_q10	(Model 6) FE_clus_q10	(Model 7) FE_NL_q10	(Model 8) FE_NL_clus_q10	(Model 9) FE_q90	(Model 10) FE_clus_q90	(Model 11) FE_NL_q90	(Model 12) FE_NL_clus_q90
Temperature	-0.0402***	-0.0402***	-0.0281**	-0.0281**	-0.0267	-0.0267***	-0.0243	-0.0243*	-0.0547	-0.0547***	-0.0322	-0.0322***
	(0.0076)	(0.0063)	(0.0132)	(0.0141)	(0.5988)	(0.0091)	(0.0607)	(0.0146)	(0.4534)	(0.0096)	(0.0533)	(0.0089)
Precipitation	0.0003**	0.0003***	0.0005**	0.0005***	0.0003	0.0003***	0.0005	0.0005	0.0003	0.0003**	0.0005	0.0005
	(0.0001)	(0.0000)	(0.0002)	(0.0001)	(0.0139)	(0.0001)	(0.0017)	(0.0005)	(0.0105)	(0.0001)	(0.0015)	(0.0003)
Temperature^2			-0.0005	-0.0005			-0.0001	-0.0001			-0.0010	-0.0010**
			(0.0004)	(0.0009)			(0.0025)	(0.0011)			(0.0022)	(0.0005)
Precipitation^2			-0.0000	-0.0000***			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Food inflation (t-1)	0.2280***	0.2280***	0.2280***	0.2280***	0.0324	0.0324	0.0325	0.0325	0.4370	0.4370***	0.4373***	0.4373***
	(0.0693)	(0.0820)	(0.0693)	(0.0819)	(1.7721)	(0.0274)	(0.1136)	(0.0273)	(1.3417)	(0.1166)	(0.0999)	(0.1167)
Food inflation (t-12)	0.0605*	0.0605	0.0606*	0.0606	0.0033	0.0033	0.0033	0.0033	0.1216	0.1216**	0.1218*	0.1218**
	(0.0319)	(0.0393)	(0.0319)	(0.0394)	(1.1925)	(0.0087)	(0.0764)	(0.0087)	(0.9028)	(0.0583)	(0.0672)	(0.0584)
Constant	0.2787	0.2787	0.2028	0.2028	-0.9776	-0.9776***	-0.9928	-0.9928***	1.6204	1.6204**	1.4834	1.4834**
	(0.2315)	(0.3764)	(0.2434)	(0.2910)	(26.6634)	(0.1097)	(1.7191)	(0.2185)	(20.1867)	(0.7553)	(1.5099)	(0.7328)
Observations	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918
Number of cross sections	186	186	186	186								
Cumulative lags of temperature	0.0509***	0.0509**	0.0510***	0.0510***	0.0509	0.0509***	0.0510	0.0510***	0.0509	0.0509***	0.0510	0.0510***
p-value	0.00366	0.0469	0.00359	0.0409	0.949	0.0147	0.354	0.0121	0.949	0.0147	0.354	0.0121

Notes: All specifications include country and year fixed effects. All models, including the term ”clus” have robust standard errors in parenthesis adjusted for clustering at the regional level. 186 countries are divided into 3 different regional statuses, i.e., tropical, subtropical and the remaining countries. Temperature is in degrees Celsius, and precipitation is in units of 100 mm.

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the macroeconomic effects of climate change assess the results with respect to whether the relevant country is advanced or developing. So, we would like to include this factor in our analysis.

To better understand if income differences and whether a country is agricultural or not matter in the relationship between climate change and food inflation, we interact temperature and precipitation with each income and agricultural dummy. Table 5 reports the impact of climate change on food price inflation in low-income and agricultural countries. The interaction coefficient between low income (income dummy=4) and temperature is positive for all clustered cases. It is statistically significant for low quantiles, indicating that the temperature effect is significantly different in low-income countries with low food price inflation. A 1° C temperature increase produces about 0.086 percentage point extra inflation in food inflation for low-income countries whose inflation is in the lower tail.

More interestingly, Table 5 indicates that precipitation has a significantly different effect in low-income countries. In low-income countries, the effect is generally significantly negative (e.g. column 4), but in those countries with low inflation rates, the effect turns positive.

Turning to the coefficients associated with the agricultural dummy, estimates are statistically insignificant, indicating no substantial heterogeneity in the effect of temperature on food price inflation between agricultural and non-agricultural countries. However, the last column of Table 5 points out that if food inflation in an agricultural country is in the upper tail, then temperature rise tends to have a deflationary impact. The estimated coefficients for the interaction dummy between agriculture and precipitation are statistically significant and positive (column 4). Hence, precipitation has an extra impact on food inflation in agricultural countries. The impact is statistically significant for the lower quantile rather than the upper quantile.

Figure 5 plots the estimated coefficients for temperature, precipitation, agricultural country dummy and the interaction term of low-income countries with temperature over the different quantiles of food price inflation. The coefficient of temperature is negative over all the quantiles, and it increases with rising food price inflation. The coefficient of precipitation is positive and gets stronger at the higher tail of food price inflation. The coefficient attached to the agricultural dummy is significantly bigger and starts negative on the lower ranges of inflation and ends up positive when the inflation is at its highest quantile. The interaction dummy between low-income countries and temperature is always negative, and it gets bigger at the higher quantiles of inflation.

Table 5: Panel regressions with interaction dummies (Cluster=region)

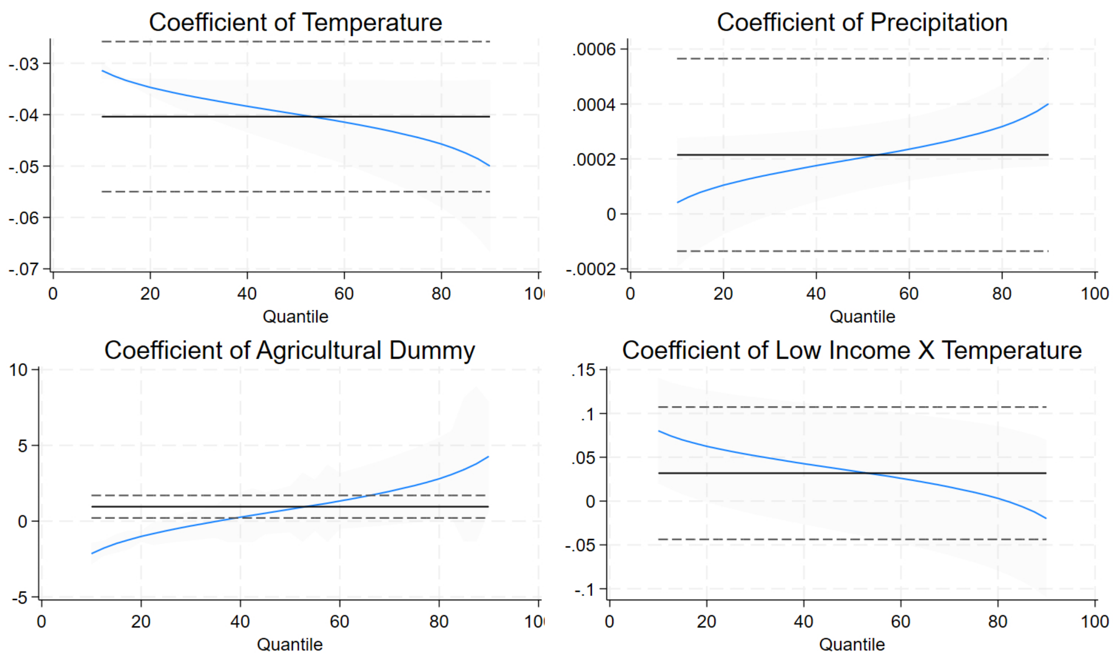
Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus	(Model 5) FE_q10	(Model 6) FE_clus_q10	(Model 7) FE_NL_q10	(Model 8) FE_NL_clus_q10	(Model 9) FE_q90	(Model 10) FE_clus_q90	(Model 11) FE_NL_q90	(Model 12) FE_NL_clus_q90
Temperature	-0.0404***	-0.0404***	-0.0260**	-0.0260**	-0.0314	-0.0314***	-0.0236	-0.0236	-0.0500	-0.0500***	-0.0286	-0.0286***
	(0.0076)	(0.0044)	(0.0119)	(0.0131)	(0.0281)	(0.0008)	(0.0520)	(0.0146)	(0.0384)	(0.0085)	(0.0539)	(0.0071)
Precipitation	0.0002*	0.0002***	0.0004*	0.0004***	0.0000	0.0000	0.0003	0.0003	0.0004	0.0004***	0.0006	0.0006*
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0008)	(0.0001)	(0.0015)	(0.0005)	(0.0011)	(0.0001)	(0.0016)	(0.0003)
Temperature^2			-0.0006	-0.0006			-0.0004	-0.0004			-0.0010	-0.0010**
			(0.0005)	(0.0007)			(0.0023)	(0.0007)			(0.0024)	(0.0005)
Precipitation^2			-0.0000	-0.0000***			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Food inflation (t-1)	0.2281***	0.2281***	0.2280***	0.2280***	0.0327	0.0327	0.0325	0.0325	0.4373***	0.4373***	0.4373***	0.4373***
	(0.0693)	(0.0819)	(0.0693)	(0.0819)	(0.0842)	(0.0274)	(0.0989)	(0.0273)	(0.1151)	(0.1169)	(0.1027)	(0.1169)
Food inflation (t-12)	0.0605*	0.0605	0.0606*	0.0606	0.0033	0.0033	0.0033	0.0033	0.1218	0.1218**	0.1219*	0.1219**
	(0.0319)	(0.0394)	(0.0319)	(0.0394)	(0.0567)	(0.0088)	(0.0665)	(0.0088)	(0.0774)	(0.0583)	(0.0691)	(0.0585)
Middle-High income dummy	-0.1792*	-0.1792	-0.2028*	-0.2028	-0.3789	-0.3789	-0.3901	-0.3901	0.0348	0.0348	-0.0022	-0.0022
	(0.1061)	(0.1337)	(0.1093)	(0.1759)	(5.0319)	(0.6287)	(8.7719)	(0.4809)	(6.8728)	(2.1661)	(9.1017)	(2.9500)
Middle-Low income dummy	0.0577	0.0577	0.1066	0.1066	0.3346	0.3346	0.3664	0.3664***	-0.2388	-0.2388	-0.1716	-0.1716
	(0.0731)	(0.0968)	(0.0824)	(0.1478)	(2.2724)	(0.2825)	(8.4156)	(0.1315)	(3.1037)	(2.0264)	(8.7320)	(2.2002)
Low income dummy	-1.3767*	-1.3767**	-1.5774*	-1.5774***	-0.5798	-0.5798	-0.6350***	-0.6350***	-2.2301	-2.2301	-2.5866***	-2.5866***
	(0.8063)	(0.5466)	(0.8334)	(0.2860)	(4.4783)	(0.8456)	(0.0302)	(0.0195)	(6.1167)	(2.4383)	(0.0307)	(0.0316)
High agricultural VA dummy	0.9545*	0.9545***	0.9136	0.9136***	-2.1442	-2.1442***	-2.2243	-2.2243***	4.2726	4.2726**	4.2742	4.2742***
	(0.5435)	(0.1685)	(0.5634)	(0.2082)	(3.1912)	(0.3564)	(4.8719)	(0.5905)	(4.3587)	(1.8321)	(5.0551)	(1.5217)
Low income $\times$ Temperature	0.0318	0.0318	0.0464	0.0464	0.0802	0.0802***	0.0863	0.0863***	-0.0200	-0.0200	0.0037	0.0037
	(0.0513)	(0.0455)	(0.0543)	(0.0307)	(0.2582)	(0.0306)	(0.3096)	(0.0161)	(0.3526)	(0.0456)	(0.3212)	(0.0363)
Low income $\times$ Precipitation	-0.0011**	-0.0011***	-0.0011*	-0.0011***	0.0015	0.0015***	0.0013	0.0013***	-0.0038	-0.0038***	-0.0036	-0.0036***
	(0.0005)	(0.0001)	(0.0006)	(0.0001)	(0.0043)	(0.0003)	(0.0050)	(0.0004)	(0.0059)	(0.0001)	(0.0052)	(0.0001)
High agricultural VA $\times$ Temperature	-0.0039	-0.0039	-0.0021	-0.0021	0.0108	0.0108	0.0143	0.0143	-0.0196	-0.0196	-0.0197	-0.0197**
	(0.0237)	(0.0090)	(0.0246)	(0.0115)	(0.0862)	(0.0265)	(0.1016)	(0.0268)	(0.1177)	(0.0134)	(0.1055)	(0.0096)
High agricultural VA $\times$ Precipitation	0.0003	0.0003***	0.0004	0.0004***	0.0005	0.0005**	0.0006	0.0006*	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0015)	(0.0002)	(0.0018)	(0.0003)	(0.0021)	(0.0001)	(0.0019)	(0.0001)
Constant	0.3473	0.3473	0.2812	0.2812	0.5188	0.5188	0.4801	0.4801	0.1635	0.1635	0.0683	0.0683
	(0.3096)	(0.4382)	(0.3141)	(0.4218)	(5.2444)	(0.5967)	(8.6291)	(0.3240)	(7.1631)	(1.7793)	(8.9535)	(2.6212)
Observations	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918
Number of cross sections	186	186	186	186								

Notes: All specifications include country and year fixed effects. All models, including the term "clus" have robust standard errors in parenthesis adjusted for clustering at the regional level. 186 countries are divided into 3 different regional statuses, i.e., tropical, subtropical and the remaining countries. Temperature is in degrees Celsius, and precipitation is in units of 100 mm.

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 5: Quantile Plot (Table 5-Model 6)



5 Robustness checks

In this section, we first consider robustness checks for including clustering using income and then clustering both income and region at the same time and conducting a two-way clustering. We use the community-contributed regression command reghdfe of Stata for using two clusters at the same time.[12] In Table 6, we check the robustness by using standard errors adjusted for clustering at the income level rather than the regional level. Table 7, on the other hand, adjusts standard errors for two-way clustering at both income and region levels.

The results are generally robust when using standard errors adjusted for clustering at the income level (Table 6). However, the estimated feedback effect for the lower quantile becomes statistically significant at the 10 percent level. In Table 7, it was not possible to attain significant results for the tails, indicating the sensitivity of the results to clustering specifications.

Table 8 presents the immediate and cumulative impact of precipitation. The bottom part of the table reports the cumulative effects, computed by summing the estimated coefficients of lagged precipitation. Including lags of precipitation does not cause substantial changes in our regression estimates. Overall, the immediate impact of precipitation is positive and significant. However, for extreme events, precipitation has a significant immediate effect when standard errors are adjusted for clustering at the regional level. There is no support for the significance of the cumulative effects, suggesting that the level effect of precipitation on inflation sums to zero and gradually disappears within a year.

These robustness checks underscore the importance of considering different clustering approaches when analysing the impact of climatic variables on inflation. The results highlight the sensitivity of the estimated effects to the chosen clustering method, particularly for extreme events and lower quantiles.

[12] See Correia (2023) for details.

Table 6: Results of Baseline equation with 1st and 12th lag of inflation: Standard errors are adjusted for clustering at income

Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus	(Model 5) FE_q10	(Model 6) FE_clus_q10	(Model 7) FE_NL_q10	(Model 8) FE_NL_clus_q10	(Model 9) FE_q90	(Model 10) FE_clus_q90	(Model 11) FE_NL_q90	(Model 12) FE_NL_clus_q90
Temperature	-0.0378***	-0.0378***	-0.0269**	-0.0269*	-0.0259	-0.0259***	-0.0252	-0.0252	-0.0506	-0.0506***	-0.0287	-0.0287***
	(0.0067)	(0.0073)	(0.0126)	(0.0159)	(0.0320)	(0.0060)	(0.0673)	(0.0205)	(0.0314)	(0.0089)	(0.0630)	(0.0069)
Precipitation	0.0003**	0.0003***	0.0005**	0.0005	0.0003	0.0003	0.0005	0.0005	0.0003	0.0003	0.0006	0.0006
	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0008)	(0.0002)	(0.0019)	(0.0004)	(0.0008)	(0.0002)	(0.0018)	(0.0006)
Temperature^2			-0.0005	-0.0005			-0.0000	-0.0000			-0.0009	-0.0009***
			(0.0004)	(0.0007)			(0.0028)	(0.0010)			(0.0027)	(0.0002)
Precipitation^2			-0.0000	-0.0000			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Food inflation (t-1)	0.2278***	0.2278***	0.2278***	0.2278***	0.0323	0.0323*	0.0322	0.0322*	0.4365***	0.4365***	0.4365***	0.4365***
	(0.0693)	(0.0863)	(0.0693)	(0.0863)	(0.0981)	(0.0187)	(0.1278)	(0.0185)	(0.0962)	(0.1392)	(0.1198)	(0.1394)
Food inflation (t-12)	0.0603*	0.0603	0.0604*	0.0604	0.0032	0.0032	0.0032	0.0032	0.1213*	0.1213**	0.1214	0.1214**
	(0.0319)	(0.0383)	(0.0319)	(0.0383)	(0.0659)	(0.0149)	(0.0859)	(0.0148)	(0.0646)	(0.0576)	(0.0805)	(0.0577)
Constant	0.9328***	0.9328***	0.8634***	0.8634***	-1.0259	-1.0259***	-1.0387	-1.0387***	3.0229***	3.0229***	2.8935***	2.8935***
	(0.1081)	(0.1578)	(0.1233)	(0.1448)	(0.8669)	(0.1058)	(1.1409)	(0.0884)	(0.8496)	(0.2052)	(1.0693)	(0.2150)
Observations	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918
Number of cross sections	186	186	186	186								

Notes: All specifications include country and year fixed effects. All models, including the term ”clus” have robust standard errors in parenthesis adjusted for clustering at the regional level. 186 countries are divided into 3 different regional statuses, i.e., tropical, subtropical and the remaining countries. Temperature is in degrees Celsius, and precipitation is in units of 100 mm.

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Results of Baseline equation with 1st and 12th lag of inflation:Standard errors are adjusted for two way clustering at region and income

Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus
Temperature	-0.0378***	-0.0378**	-0.0269***	-0.0269
	(0.0055)	(0.0087)	(0.0088)	(0.0132)
Precipitation	0.0003**	0.0003*	0.0005**	0.0005
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Temperature^2			-0.0005	-0.0005
			(0.0004)	(0.0010)
Precipitation^2			-0.0000	-0.0000
			(0.0000)	(0.0000)
Food price inflation (t-1)	0.2278***	0.2278	0.2278***	0.2278
	(0.0270)	(0.0855)	(0.0270)	(0.0860)
Food price inflation (t-12)	0.0603***	0.0603	0.0604***	0.0604
	(0.0173)	(0.0444)	(0.0173)	(0.0469)
Constant	1.0636***	1.0636**	1.0448***	1.0448**
	(0.1095)	(0.1688)	(0.1117)	(0.2267)
Observations	48,918	48,918	48,918	48,918
R-squared	0.1476	0.1476	0.1477	0.1477

Notes: All specifications include country and year fixed effects. All models, including the term ”clus” have robust standard errors in parenthesis adjusted for clustering. Temperature is in degrees Celsius, and precipitation is in units of 100 mm.
Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Results of Baseline equation with lags: Cumulative effect of precipitation

Coefficients	(Model 1) FE	(Model 2) FE_clus	(Model 3) FE_NL	(Model 4) FE_NL_clus	(Model 5) FE_q10	(Model 6) FE_clus_q10	(Model 7) FE_NL_q10	(Model 8) FE_NL_clus_q10	(Model 9) FE_q90	(Model 10) FE_clus_q90	(Model 11) FE_NL_q90	(Model 12) FE_NL_clus_q90
Temperature	-0.0381***	-0.0381***	-0.0272**	-0.0272**	-0.0262	-0.0262**	-0.0252	-0.0252*	-0.0507	-0.0507***	-0.0294	-0.0294***
	(0.0067)	(0.0086)	(0.0127)	(0.0127)	(0.0269)	(0.0107)	(0.0480)	(0.0140)	(0.0311)	(0.0093)	(0.0484)	(0.0078)
Precipitation	0.0003**	0.0003***	0.0005**	0.0005***	0.0003	0.0003***	0.0005	0.0005	0.0003	0.0003***	0.0006	0.0006**
	(0.0001)	(0.0000)	(0.0002)	(0.0002)	(0.0006)	(0.0001)	(0.0014)	(0.0005)	(0.0007)	(0.0001)	(0.0014)	(0.0003)
Temperature^2			-0.0005	-0.0005			-0.0000	-0.0000			-0.0009	-0.0009*
			(0.0004)	(0.0010)			(0.0020)	(0.0011)			(0.0020)	(0.0005)
Precipitation^2			-0.0000*	-0.0000***			-0.0000	-0.0000			-0.0000	-0.0000
			(0.0000)	(0.0000)			(0.0000)	(0.0000)			(0.0000)	(0.0000)
Food inflation (t-1)	0.2277***	0.2277***	0.2277***	0.2277***	0.0313	0.0313	0.0314	0.0314	0.4370***	0.4370***	0.4375***	0.4375***
	(0.0693)	(0.0820)	(0.0694)	(0.0819)	(0.0823)	(0.0271)	(0.0913)	(0.0270)	(0.0952)	(0.1169)	(0.0920)	(0.1171)
Food inflation (t-12)	0.0604*	0.0604	0.0604*	0.0604	0.0029	0.0029	0.0030	0.0030	0.1216*	0.1216**	0.1218**	0.1218**
	(0.0318)	(0.0390)	(0.0318)	(0.0391)	(0.0553)	(0.0084)	(0.0613)	(0.0085)	(0.0639)	(0.0581)	(0.0618)	(0.0582)
Constant	0.9371***	0.9371***	0.8682***	0.8682***	-1.0248	-1.0248***	-1.0367	-1.0367***	3.0273***	3.0273***	2.9048***	2.9048***
	(0.1121)	(0.0953)	(0.1255)	(0.0469)	(0.7294)	(0.1895)	(0.8158)	(0.0789)	(0.8431)	(0.0643)	(0.8221)	(0.0899)
Observations	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918	48,918
Number of cross sections	186	186	186	186								
Cumulative lags of prep	-6.87e-06	-6.87e-06	-2.18e-05	-2.18e-05	-6.87e-06	-6.87e-06	-2.18e-05	-2.18e-05	-6.87e-06	-6.87e-06	-2.18e-05	-2.18e-05
p-value	0.987	0.976	0.958	0.919	0.995	0.971	0.984	0.901	0.995	0.971	0.984	0.901

Notes: All specifications include country and year fixed effects. All models, including the term ”clus” have robust standard errors in parenthesis adjusted for clustering at the regional level. 186 countries are divided into 3 different regional statuses, i.e., tropical, subtropical and the remaining countries. Temperature is in degrees Celsius and precipitation is in units of 100 mm.
Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6 Conclusion

In this study, we examine the effects of seasonally adjusted temperature and precipitation on food price inflation across 186 countries from 2000 to 2022, using monthly data. We use both panel-fixed effects and quantile regressions to report our results. Our findings indicate that an increase in monthly temperature significantly impacts food price inflation both immediately and persistently. Although the effect of precipitation is also significant, it is less severe. These results align with the existing literature on the relationship between food price inflation and weather variables.

Our results illustrate that the contemporaneous impact of a temperature change on inflation is usually negative, which can be attributed to the temperature change's non-coincidence with the immediate realisation of inflationary effects. This initial negative impact likely reflects short-term disruptions and adjustments that do not immediately translate into price changes. However, our analysis reveals that inflation continues to respond to temperature changes even after the initial shock has dissipated. Over time, the cumulative effects of these temperature changes result in elevated levels of inflation. Meanwhile, we find the contemporaneous impact of a precipitation change on inflation is positive.

These findings are consistent with previous studies, such as those by Mukherjee and Ouattara (2021) and Kotz et al. (2024), which document the persistent impacts of temperature increases on inflation. Our study further demonstrates that the immediate effect of a temperature rise is more pronounced when inflation is already at a higher level. This suggests that countries experiencing higher initial inflation rates are more vulnerable to immediate inflationary pressures from temperature shocks.

Moreover, the cumulative effects of temperature increases are found to be significantly inflationary across all quantiles of inflation. This implies that while the immediate impacts may vary depending on the pre-existing inflationary environment, the long-term effects of temperature increases uniformly contribute to higher inflation. This underscores the importance of considering both immediate and cumulative impacts in assessing the overall economic consequences of climate change. Our findings highlight the necessity for policymakers to account for the temporal dynamics of climate impacts on inflation. Immediate policy responses may need to be tailored to mitigate the short-term disruptions, while long-term strategies should focus on addressing the persistent inflationary pressures induced by climatic changes.

We also show that the impact of temperature and precipitation shocks may vary with respect to the income level and the share of the agricultural sector in total economic activity. Such heterogeneity is also noted in the literature. In addition, this study suggests that the level of inflation across countries may cause them to respond differently to climate shocks even if they have the same income level or agricultural sector size. Our findings strongly suggest that a change in temperature and precipitation levels leads to a heterogeneous response to inflation, depending on whether the country is already struggling with high or low inflation. For countries that already have high levels of inflation, temperature changes can create persistent pressures on inflation, complicating the food pricing dynamics within and between countries. With progressing climate change, we should expect a more diverse response of inflation to weather shocks.

Our results have two important policy implications. First, food prices and price volatility can directly contribute to aggregate inflation, which is a primary concern of monetary policy. Second, the relationship between high food prices and aggregate inflation is multifaceted. Elevated food prices can erode purchasing power, disproportionately affecting lower-income households that spend a larger share of their income on food. This can lead to increased poverty and food insecurity, exacerbating social inequalities. Furthermore, price volatility can create uncertainty in markets, disrupt supply chains and lead to inefficiencies in resource allocation. For central banks, these dynamics present a dual challenge: maintaining price stability while also addressing the broader economic implications of climate-induced price shocks.

The results of our paper can be interpreted as a warning for policymakers, i.e. monetary policy should more comprehensively consider the risks created by climate change. Traditional models of inflation forecasting and policy analysis may need to be adapted to account for the increased uncertainty and long-term impacts associated with climate change. This could involve integrating climate scenarios into economic models, improving the monitoring of climate-related risks, and coordinating with other policy areas, such as fiscal policy and environmental regulation, to mitigate the economic impacts of climate change.

This study can be extended in several ways. First, while the literature generally agrees on the impact of climate change on inflation, conclusions are often driven by mean or median values. The present study highlights the increasing uncertainty in inflation due to advancing climate change. Not only inflation but also the frequency and intensity of climate shocks vary across regions and over time. Examining the economic consequences of this volatility would significantly enhance our understanding of the effects of climate change. Furthermore, future research could investigate the effects of climate change on the subcomponents of consumer prices using quantile regression. This approach would allow for the dynamic effects of climate shocks to be uncovered across different segments of consumer price inflation, providing a more detailed and nuanced analysis.

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Appendices

Descriptive statistics

Table A1: Seasonally adjusted temperature (Average of 2000-2022)

Rank	Country	Average Temperature	Rank	Country	Average Temperature
1	Greenland	-18.4225	94	Iraq	23.1715
2	Canada	-4.01363	95	China, Hong Kong SAR	23.301
3	Russian Federation	-3.60655	96	Egypt	23.3126
4	Mongolia	1.1387	97	Uganda	23.3987
5	Iceland	2.08637	98	Ethiopia	23.515
6	Norway	2.38155	99	Mauritius	23.5295
7	Finland	2.65978	100	Algeria	23.7157
8	Kyrgyzstan	2.91689	101	Guatemala	23.7801
9	Sweden	3.37905	102	Paraguay	24.0082
10	Tajikistan	4.13413	103	Lao People's Democratic Republic	24.1965
11	Estonia	6.50351	104	French Polynesia	24.3377
12	Switzerland	6.66516	105	Mozambique	24.4875
13	Latvia	7.03456	106	Vanuatu	24.5019
14	Kazakhstan	7.32226	107	Dominican Republic	24.5504
15	Lithuania	7.5495	108	Timor-Leste	24.6037
16	Austria	7.63589	109	Sao Tome and Principe	24.6137
17	Belarus	7.6598	110	Cook Islands	24.704
18	China, mainland	7.71361	111	Papua New Guinea	24.741
19	Armenia	8.06411	112	Equatorial Guinea	24.7815
20	Andorra	8.42773	113	Honduras	24.7999
21	Czechia	8.82849	114	Fiji	24.8096
22	Poland	9.01171	115	Viet Nam	24.8199
23	Slovakia	9.07752	116	Costa Rica	24.8494
24	Denmark	9.10728	117	Congo	24.8806
25	Georgia	9.28066	118	Cameroon	24.9163
26	United Kingdom of Great Britain and Northern Ireland	9.35127	119	Haiti	24.9565
27	Chile	9.44741	120	Colombia	25.0417
28	Ukraine	9.54653	121	India	25.051
29	United States of America	9.57851	122	Puerto Rico	25.0628
30	Ireland	9.7626	123	Tonga	25.1059
31	Germany	9.78823	124	Kenya	25.2091
32	Slovenia	10.0713	125	El Salvador	25.3327
33	Montenegro	10.1967	126	Gabon	25.3361
34	Luxembourg	10.2118	127	Brazil	25.5649
35	Romania	10.4801	128	Panama	25.614
36	Bhutan	10.5057	129	Bahamas	25.6505
37	Bosnia and Herzegovina	10.6262	130	Bangladesh	25.7668
38	New Zealand	10.6778	131	Montserrat	25.7808
39	Netherlands (Kingdom of the)	10.6979	132	Belize	25.8367
40	Belgium	10.8566	133	Solomon Islands	25.9147
41	North Macedonia	11.0445	134	Nicaragua	25.9309
42	Republic of Moldova	11.1756	135	Jamaica	25.9316
43	Bulgaria	11.6592	136	Indonesia	26.004
44	Serbia	11.6974	137	Guinea	26.0131
45	Hungary	11.7723	138	Saudi Arabia	26.1472
46	France	11.8187	139	Saint Vincent and the Grenadines	26.2148
47	Japan	11.8711	140	Philippines	26.3329
48	Turkey	11.9075	141	Malaysia	26.4314
49	Croatia	12.2075	142	Grenada	26.5464
50	Republic of Korea	12.2962	143	Kuwait	26.5906
51	Lesotho	12.5138	144	Trinidad and Tobago	26.5966
52	Albania	12.6756	145	Barbados	26.6342
53	San Marino	13.0566	146	Suriname	26.6477
54	Azerbaijan	13.222	147	Sierra Leone	26.6797
55	Italy	13.4119	148	Dominica	26.8726
56	Afghanistan	13.6282	149	Thailand	26.8761
57	Uzbekistan	13.9651	150	Cote d'Ivoire	26.9202
58	Spain	14.2114	151	Brunei Darussalam	26.9852
59	Nepal	14.2922	152	Somalia	27.0193
60	Greece	14.496	153	Saint Lucia	27.0387
61	Argentina	15.1836	154	Seychelles	27.1844
62	Lebanon	15.6772	155	Antigua and Barbuda	27.2299
63	Portugal	15.962	156	Sri Lanka	27.3227
64	Uruguay	18.0634	157	Micronesia (Federated States of)	27.4212
65	Morocco	18.3188	158	Cambodia	27.4267
66	South Africa	18.3665	159	Nigeria	27.429
67	Iran (Islamic Republic of)	18.5974	160	Saint Kitts and Nevis	27.5032
68	Cyprus	19.213	161	Togo	27.5415
69	Rwanda	19.2878	162	Samoa	27.6558
70	Peru	19.7152	163	Chad	27.7122
71	Jordan	19.7263	164	Anguilla	27.7315
72	Malta	19.7581	165	Singapore	27.7658
73	Israel	20.1936	166	Kiribati	27.7873
74	Namibia	20.4999	167	Oman	27.7977
75	Burundi	20.5607	168	Ghana	27.8232
76	Tunisia	20.7226	169	Cayman Islands	27.8587
77	Bolivia (Plurinational State of)	20.7286	170	Guam	27.9084
78	Ecuador	21.4064	171	Bahrain	27.9947
79	Mexico	21.4203	172	Palau	28.0027
80	Pakistan	21.6066	173	Guinea-Bissau	28.1016
81	Bermuda	21.6165	174	Maldives	28.1118
82	Angola	21.7624	175	Niger	28.1119
83	Zimbabwe	21.9645	176	Benin	28.2218
84	Australia	22.126	177	Qatar	28.3141
85	Botswana	22.1703	178	United Arab Emirates	28.3934
86	Zambia	22.2209	179	Curacao	28.4456
87	Cabo Verde	22.5995	180	Gambia	28.5024
88	Malawi	22.7085	181	Djibouti	28.6181
89	Madagascar	22.7534	182	Mauritania	28.932
90	New Caledonia	22.7998	183	Senegal	29.0352
91	Libya	22.8822	184	Aruba	29.2154
92	United Republic of Tanzania	22.9835	185	Mali	29.3185
93	China, Macao SAR	23.1216	186	Burkina Faso	29.4243

Table A2: Seasonally adjusted precipitation (Average of 2000-2022)

Rank	Country	Average Precipitation	Rank	Country	Average Precipitation
1	Egypt	1.58416	94	Saint Kitts and Nevis	90.9624
2	Libya	3.04119	95	Georgia	91.1569
3	Oman	4.14045	96	Bolivia (Plurinational State of)	91.467
4	United Arab Emirates	4.56333	97	Bosnia and Herzegovina	91.9911
5	Qatar	5.17363	98	Norway	94.2066
6	Bahrain	5.98126	99	Austria	94.4094
7	Algeria	6.77072	100	India	94.5053
8	Saudi Arabia	8.03786	101	Paraguay	95.2152
9	Jordan	8.71642	102	Albania	95.8072
10	Kuwait	8.72337	103	Bahamas	97.3267
11	Mauritania	9.58924	104	Nigeria	98.3207
12	Niger	15.4792	105	United Kingdom of Great Britain and Northern Ireland	98.9496
13	Iraq	15.5076	106	Rwanda	100.436
14	Iran (Islamic Republic of)	17.0034	107	Ireland	100.578
15	Cabo Verde	17.0703	108	Iceland	101.564
16	Uzbekistan	17.7848	109	Switzerland	101.675
17	Djibouti	18.2405	110	Togo	101.738
18	Mongolia	18.4995	111	Ghana	102.191
19	Israel	21.6831	112	Burundi	103.427
20	Kazakhstan	21.6898	113	Timor-Leste	104.62
21	Tunisia	21.948	114	Uruguay	107.456
22	Somalia	23.7423	115	Nepal	107.887
23	Namibia	24.5275	116	Uganda	109.092
24	Pakistan	24.9875	117	Cote d'Ivoire	110.513
25	Morocco	25.8307	118	Montenegro	110.609
26	Afghanistan	26.874	119	French Polynesia	113.455
27	Mali	27.8309	120	Republic of Korea	115.346
28	Chad	30.0965	121	Slovenia	117.389
29	Botswana	33.7237	122	Kiribati	117.528
30	Aruba	36.7781	123	Madagascar	120.839
31	Malta	38.6694	124	Bermuda	121.786
32	South Africa	39.047	125	Cayman Islands	121.85
33	Greenland	39.2833	126	Dominican Republic	125.707
34	Cyprus	39.7406	127	Barbados	126.754
35	Australia	40.1806	128	Haiti	129.144
36	Kyrgyzstan	40.1945	129	New Zealand	132.622
37	Russian Federation	40.216	130	Peru	133.207
38	Republic of Moldova	40.6858	131	Cameroon	135.429
39	Azerbaijan	41.2747	132	Grenada	135.625
40	Canada	45.5465	133	Montserrat	135.821
41	Ukraine	46.3169	134	Seychelles	135.844
42	Armenia	46.8244	135	Congo	136.699
43	Curacao	48.5764	136	Thailand	137.007
44	Turkey	49.7109	137	Japan	137.785
45	Argentina	49.9785	138	El Salvador	138.859
46	Finland	50.4554	139	Guinea-Bissau	140.264
47	China, mainland	50.8826	140	New Caledonia	140.538
48	Poland	50.911	141	Tonga	145.887
49	Hungary	51.0383	142	Viet Nam	147.244
50	Spain	51.8904	143	Sri Lanka	147.547
51	Romania	53.6768	144	Brazil	148.192
52	Belarus	53.8412	145	Guinea	150.026
53	Sweden	54.5208	146	Honduras	153.314
54	Lebanon	55.0418	147	Lao People's Democratic Republic	154.486
55	Bulgaria	55.8004	148	Bhutan	155.034
56	Estonia	55.8355	149	Gabon	156.087
57	Tajikistan	55.9068	150	Cambodia	160.578
58	Czechia	56.7299	151	China, Macao SAR	161.56
59	North Macedonia	56.9038	152	Trinidad and Tobago	166.089
60	Greece	56.9258	153	Cook Islands	167.055
61	Latvia	56.9609	154	Jamaica	167.718
62	Zimbabwe	57.0755	155	Mauritius	171.342
63	Lithuania	57.1005	156	Puerto Rico	171.39
64	Germany	60.4535	157	Saint Lucia	171.747
65	Denmark	61.0425	158	Belize	174.962
66	United States of America	61.711	159	Ecuador	175.564
67	Senegal	62.2175	160	China, Hong Kong SAR	176.062
68	Serbia	63.4319	161	Dominica	176.546
69	Kenya	63.433	162	Bangladesh	177.026
70	Slovakia	64.0894	163	Guatemala	180.9
71	Mexico	64.4959	164	Maldives	183.146
72	San Marino	65.7993	165	Sao Tome and Principe	190.454
73	Lesotho	66.221	166	Nicaragua	191.389
74	Italy	66.2613	167	Suriname	194.409
75	Netherlands (Kingdom of the)	66.6654	168	Panama	203.805
76	France	68.6868	169	Guam	205.736
77	Burkina Faso	70.1596	170	Saint Vincent and the Grenadines	206.469
78	Portugal	72.1241	171	Equatorial Guinea	208.4
79	Ethiopia	72.4137	172	Singapore	213.405
80	Belgium	74.9163	173	Colombia	217.474
81	Chile	75.4978	174	Sierra Leone	221.478
82	Luxembourg	78.4104	175	Fiji	222.13
83	United Republic of Tanzania	79.8806	176	Philippines	228.919
84	Mozambique	81.797	177	Vanuatu	230.315
85	Andorra	84.9084	178	Indonesia	236.678
86	Zambia	85.0413	179	Costa Rica	246.752
87	Gambia	85.5584	180	Malaysia	256.909
88	Benin	86.7411	181	Papua New Guinea	260.785
89	Angola	87.9853	182	Solomon Islands	265.313
90	Antigua and Barbuda	88.0692	183	Samoa	265.842
91	Malawi	88.4026	184	Brunei Darussalam	284.525
92	Anguilla	88.5845	185	Palau	297.306
93	Croatia	90.7543	186	Micronesia (Federated States of)	335.721

Table A3: Seasonally adjusted food price inflation (Average of 2000-2022)

Rank	Country	Average Precipitation	Rank	Country	Average Precipitation
1	Switzerland	0.035503	94	Philippines	0.359253
2	Ireland	0.062883	95	Equatorial Guinea	0.364825
3	Brunei Darussalam	0.071567	96	Algeria	0.370208
4	Japan	0.084726	97	Armenia	0.378314
5	Cook Islands	0.145585	98	Estonia	0.384214
6	Norway	0.157052	99	Guam	0.385498
7	New Caledonia	0.173362	100	Samoa	0.392875
8	France	0.175273	101	Djibouti	0.392932
9	Israel	0.178181	102	Libya	0.398751
10	Qatar	0.180149	103	Togo	0.402836
11	Belize	0.184282	104	Bulgaria	0.411349
12	Portugal	0.184333	105	Turkey	0.42376
13	Netherlands (Kingdom of the)	0.185154	106	Cameroon	0.426163
14	Montserrat	0.186902	107	Latvia	0.429214
15	Cambodia	0.187183	108	Bolivia (Plurinational State of)	0.430381
16	Denmark	0.188709	109	China, Hong Kong SAR	0.433411
17	Singapore	0.194818	110	San Marino	0.436322
18	Italy	0.198933	111	Solomon Islands	0.439653
19	Finland	0.20142	112	Seychelles	0.453697
20	Greece	0.201896	113	India	0.466774
21	Bahamas	0.202324	114	Honduras	0.470968
22	Sweden	0.204373	115	Trinidad and Tobago	0.471637
23	Kiribati	0.206507	116	Maldives	0.471803
24	Cyprus	0.207327	117	Mauritius	0.474323
25	Morocco	0.21158	118	Mexico	0.48976
26	Gabon	0.211921	119	Barbados	0.514045
27	Micronesia (Federated States of)	0.212828	120	Bhutan	0.514355
28	Puerto Rico	0.213329	121	Mauritania	0.515881
29	New Zealand	0.215651	122	Curacao	0.526886
30	Bahrain	0.216223	123	Bangladesh	0.529608
31	United States of America	0.216254	124	Hungary	0.533549
32	Chile	0.217267	125	Iraq	0.53565
33	Germany	0.217601	126	Botswana	0.539284
34	Greenland	0.219999	127	South Africa	0.567885
35	Saint Lucia	0.220815	128	Congo	0.573158
36	Andorra	0.221339	129	Indonesia	0.576825
37	Luxembourg	0.224277	130	Romania	0.57907
38	Belgium	0.225114	131	Viet Nam	0.581472
39	Austria	0.225389	132	Uganda	0.58368
40	Oman	0.225641	133	Namibia	0.593207
41	Benin	0.231165	134	Somalia	0.596168
42	Saint Kitts and Nevis	0.232616	135	Kyrgyzstan	0.596217
43	French Polynesia	0.232767	136	Nepal	0.596622
44	United Kingdom of Great Britain and Northern Ireland	0.233554	137	Georgia	0.606681
45	Grenada	0.237705	138	Cote d'Ivoire	0.610174
46	Panama	0.238642	139	Brazil	0.61521
47	Croatia	0.238684	140	Paraguay	0.630325
48	Australia	0.239186	141	Azerbaijan	0.637537
49	Tonga	0.239623	142	Gambia	0.65092
50	Cayman Islands	0.240316	143	Dominican Republic	0.655234
51	Mali	0.241685	144	Nicaragua	0.65638
52	Bosnia and Herzegovina	0.245456	145	United Republic of Tanzania	0.668084
53	Spain	0.248383	146	Guatemala	0.672728
54	Dominica	0.249084	147	Madagascar	0.677965
55	Czechia	0.253417	148	Afghanistan	0.68116
56	Malaysia	0.253815	149	Lesotho	0.695869
57	Bermuda	0.257469	150	Rwanda	0.717993
58	Antigua and Barbuda	0.262047	151	Burundi	0.731536
59	Montenegro	0.265475	152	Pakistan	0.732596
60	Canada	0.266163	153	Ecuador	0.733412
61	United Arab Emirates	0.266195	154	Kazakhstan	0.743672
62	Niger	0.266879	155	Republic of Moldova	0.754638
63	Jordan	0.267821	156	Jamaica	0.777795
64	Saint Vincent and the Grenadines	0.269046	157	Uruguay	0.785869
65	Senegal	0.270251	158	Mongolia	0.787543
66	Papua New Guinea	0.271336	159	Lao People's Democratic Republic	0.801336
67	North Macedonia	0.272081	160	Mozambique	0.823841
68	Costa Rica	0.27482	161	Kenya	0.829673
69	Timor-Leste	0.282945	162	Sierra Leone	0.839312
70	Slovakia	0.289104	163	Russian Federation	0.841933
71	Anguilla	0.289788	164	Ukraine	0.910676
72	Burkina Faso	0.298251	165	Tunisia	0.914748
73	Palau	0.298283	166	Thailand	0.937923
74	Chad	0.300582	167	Sri Lanka	0.955863
75	Peru	0.302656	168	Egypt	0.97047
76	Poland	0.306182	169	Zambia	0.981611
77	Guinea-Bissau	0.306724	170	Serbia	1.0468
78	Saudi Arabia	0.307805	171	Uzbekistan	1.06141
79	Slovenia	0.309672	172	Haiti	1.08485
80	Cabo Verde	0.310741	173	Nigeria	1.08591
81	El Salvador	0.312097	174	Sao Tome and Principe	1.09627
82	China, Macao SAR	0.314014	175	Malawi	1.11538
83	Republic of Korea	0.31598	176	Ghana	1.12682
84	China, mainland	0.32056	177	Ethiopia	1.17492
85	Malta	0.325969	178	Guinea	1.24833
86	Albania	0.332992	179	Tajikistan	1.42755
87	Iceland	0.335825	180	Argentina	1.53896
88	Vanuatu	0.340129	181	Suriname	1.57901
89	Aruba	0.344824	182	Belarus	1.62807
90	Colombia	0.348865	183	Iran (Islamic Republic of)	1.81427
91	Fiji	0.355313	184	Lebanon	1.96889
92	Kuwait	0.356625	185	Zimbabwe	2.0508
93	Lithuania	0.358938	186	Angola	2.25786