

Weather Shocks and Inflation in Mexico: A Regime-Specific Analysis

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Abstract

This paper examines the impact of weather shocks on inflation in Mexico, under stable and anomalous weather regimes. To analyze these effects, I construct an aggregate climate index inspired by the Actuaries Climate Index and integrate it into a regime-switching SVAR model. The findings reveal that weather shocks increase headline inflation, primarily through the non-core component, while core inflation remains largely unaffected. Notably, the impact of these shocks is amplified during anomalous weather regimes. These results emphasize that weather-related relative price changes primarily reflect temporary supply shocks, rather than persistent shifts in underlying inflation.

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1 Introduction

Countries often face significant challenges due to climate variability and its increasing effects on economic outcomes. Extreme weather events, often associated with El Niño, La Niña, and climate change, disrupt agriculture and potentially other industries, contributing to fluctuations in food and energy prices and ultimately affecting inflation. These effects are relevant across economies, as unusual weather patterns can contribute to relative price changes that alter the assessment of inflation dynamics and short-term economic stability.

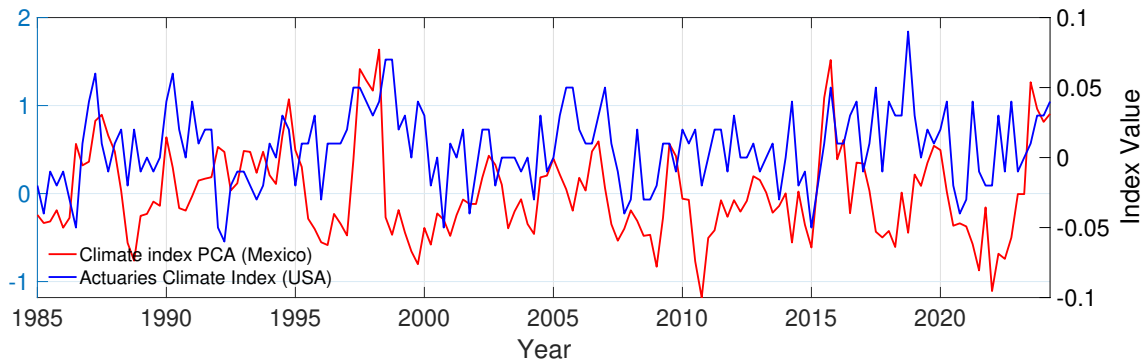
Given the importance of understanding these dynamics, this study examines the macroeconomic effects of weather shocks on inflation and other economic variables in Mexico. The analysis begins by constructing an aggregate weather index inspired by the Actuaries Climate Index (ACI) for the United States and Canada. To do it, I combine data on El Niño and La Niña oscillations, precipitation, and temperature anomalies for Mexico. Furthermore, I standardize these variables and use Principal Component Analysis to create a composite index that captures overall weather dynamics, similar to the methodology employed in the construction of the ACI.

Figure 1 compares the Mexican Climate Index and the Actuaries Climate Index (ACI) for the United States and reveals a moderate comovement, with correlations peaking at short horizons. This pattern suggests that large-scale climate phenomena generate partially synchronized weather dynamics across countries, while still allowing for substantial country-specific variation in the realization of climate shocks. These differences motivate the use of a Mexico-specific climate index in the empirical analysis that follows.¹

Next, I use regime-switching models based on [Baumeister et al. \(2021\)](#) and [Baumeister et al. \(2024\)](#) to identify distinct weather phases and classify them as *anomalous* or *stable*. The classification is data-driven: the anomalous regime captures periods with persistently higher

¹A more detailed description of the underlying variables, data sources, and index construction is provided in Section 3.

Figure 1: Mexican Climate Index and the Actuaries Climate Index for the United States



Notes. The Mexican climate index is constructed using Principal Component Analysis (PCA) applied to a set of standardized climate-related variables: the El Niño and La Niña components of the Multivariate ENSO Index (MENSO), positive and negative precipitation anomalies measured over a 12-month horizon, and temperature anomalies defined as deviations from a 60-month moving average. A detailed description of the procedure is provided in Section 3.

The Actuaries Climate Index (ACI) for the United States is a composite indicator designed to monitor the frequency and intensity of extreme weather conditions. It combines six standardized components: high and low temperature extremes, heavy rainfall, drought (consecutive dry days), high wind, and sea level changes, all measured relative to a 1961–1990 reference period. Each component is expressed as a standardized anomaly, and the ACI is computed as the average of these anomalies. See [American Academy of Actuaries and Canadian Institute of Actuaries and Casualty Actuarial Society and Society of Actuaries \(2020\)](#).

weather index values, while the stable regime captures periods with lower average values. Unlike traditional regime-switching models with fixed regime-specific means, this approach allows the conditional mean to evolve over time within each regime. This added flexibility is especially relevant in the context of climate change, as it accommodates gradual shifts in underlying weather conditions without arbitrarily increasing the number of regimes.

Using the weather index, I then estimate a Structural Vector Autoregression (SVAR) model to quantify the effects of weather shocks on inflation and other macroeconomic variables during stable and anomalous weather regimes. The SVAR model incorporates exogenous variables and conditions on regimes, following a similar approach to [Angeles et al. \(2019\)](#). Additionally, it extends the analysis by introducing differential weather effects across weather regimes, building on the framework of [Kim et al. \(2024\)](#). The results indicate that weather shocks have a modest positive effect on headline and non-core inflation. However, the effects are more pronounced during anomalous weather regimes. Core inflation remains unaffected, as expected, given its exclusion of components more vulnerable to weather-related shocks, such as food prices.

This study contributes to the growing literature on the macroeconomic effects of weather shocks, in line with [Kim et al. \(2024\)](#) and [Ventosa-Santaulària et al. \(2024\)](#). [Kim et al. \(2024\)](#) document persistent and time-varying inflation responses to severe weather in the United States, driven primarily by food- and energy-related price dynamics and limited adaptation. In a similar spirit, this paper finds nonlinear inflation responses to weather shocks in Mexico, with stronger effects during periods of anomalous weather. The evidence suggests that climate shocks operate mainly through price components directly exposed to weather conditions, while leaving core inflation dynamics broadly unchanged. Notably, the responses are identified at the national level, which is particularly important in a country as geographically and climatically diverse as Mexico. These results suggest that weather-driven supply shocks are not only local disturbances but can propagate broadly enough to shape aggregate inflation

dynamics.

[Ventosa-Santaulària et al. \(2024\)](#), focus on Mexico and employ a nonlinear local projection approach to study inflation dynamics under El Niño- and La Niña-induced weather regimes. Their results highlight that extreme weather events increase prices, with the strongest effects observed in agricultural ones. By contrast, this paper adopts a regime-switching SVAR framework ([Sims 1980](#); [Hamilton 1989](#)) to identify the dynamic effects of weather shocks on headline, core, and non-core inflation. My results indicate that extreme weather shocks mainly raise inflation through the non-core component.

In contrast to [Kim et al. \(2024\)](#), who analyze a longer time horizon to study aggregate macroeconomic effects of severe weather in the United States, this paper focuses on Mexico and employs a regime-dependent SVAR model to capture inflation dynamics under stable and anomalous weather regimes. Despite the shorter timeframe dictated by data limitations, the results also point to more pronounced relative price changes during anomalous periods. Compared with [Ventosa-Santaulària et al. \(2024\)](#), who link El Niño and La Niña regimes to demand-driven inflation dynamics, my framework directly identifies the effects of weather shocks across headline, core, and non-core inflation.

Literature Review There is recent evidence that adverse weather shocks impact inflation. [Parker \(2018\)](#) examines the effects of natural disasters on inflation across 212 economies using a panel regression approach. The study finds that the inflationary impact varies by disaster type, severity, and economic development level. Storms, floods, and droughts significantly increase inflation in developing economies, particularly in food and energy prices, while having negligible effects in advanced economies. [Cashin et al. \(2017\)](#) demonstrate that El Niño events lead to substantial inflationary effects, particularly in countries with high food shares in their CPI, driven by agricultural supply constraints. A previously mentioned, [Ventosa-Santaulària et al. \(2024\)](#) find that adverse weather conditions, such as those linked

to El Niño and La Niña, intensify inflation responses to aggregate demand shocks, with agricultural inflation showing the most pronounced increases.

In their study, [Abril-Salcedo et al. \(2020\)](#) examine the impact of extreme weather events on inflation subindices in Colombia. Using a Smooth Transition Regression model, their findings reveal that significant El Niño episodes can lead to an increase in food inflation of up to 730 basis points within a year. In contrast, the effects of La Niña appear to be less pronounced and more ambiguous. Extending their results, [Melo-Velandia et al. \(2022\)](#) apply a non-stationary Extreme Value Theory approach and conclude that extreme El Niño events dramatically increase the risk of perishable food price spikes, in some cases multiplying by five the probability of high inflation episodes. The evidence from Colombia further illustrates the nonlinear responses of inflation to climate shocks, consistent with my results that weather regimes shape the magnitude of relative price adjustments.

In six Latin American countries, including Mexico, [Köse and Ünal \(2024\)](#) show that oil price shocks, exchange rate fluctuations, and temperature changes significantly drive food inflation. In a broader study involving over 100 countries, [Qi et al. \(2025\)](#) find that climate risk indices have strong short-term inflationary effects. While the impact lessens over the long term, it remains significant in low-income economies. In their study, they identify two main transmission channels: first, climate shocks worsen economic conditions, prompting central banks to lower interest rates. This expansionary policy amplifies inflation. Second, climate shocks directly increase food inflation by reducing agricultural output.

Similarly, [Kim et al. \(2024\)](#) investigate the macroeconomic effects of severe weather shocks in the United States using a nonlinear VAR framework and a novel severe weather index. They find robust evidence of time-varying effects, with shocks causing significant reductions in industrial production and consumption growth and increases in unemployment and inflation, particularly in recent decades. The results suggest limited adaptation to the increasing frequency and intensity of severe weather.

While much of the recent literature emphasizes the inflationary effects of weather shocks, several studies have also documented their impact on economic growth, suggesting an additional channel through which climate variability may influence price dynamics. [Dell et al. \(2012\)](#) examine the impact of temperature fluctuations on economic growth across countries and find that higher temperatures reduce growth rates in poorer nations by affecting agricultural and industrial outputs as well as political stability. Similarly, [Colacito et al. \(2019\)](#) show that seasonal temperature increases adversely affect U.S. economic activity, with higher summer temperatures reducing state-level output growth, particularly in hotter regions. [Hsiang \(2016\)](#) reviews recent advances in climate econometrics and shows that weather shocks have broad causal effects on growth, agricultural yields, labor productivity, energy demand, and even conflict, with impacts that are nonlinear, heterogeneous, and only partially mitigated by adaptation.

2 Econometric Models

This section details the empirical strategy for analyzing the effects of weather shocks within a regime-dependent framework. I employ a Structural Vector Autoregression (SVAR) model in the tradition of [Sims \(1980\)](#) and an exogenous identification of weather regimes using a regime-switching regression with time-varying means, as in [Hamilton \(1989\)](#) and further developed by [Baumeister et al. \(2024\)](#) and [Leiva-León et al. \(2024\)](#). This approach classifies weather patterns into two distinct regimes: a stable regime and an anomalous regime. To identify structural shocks, I rely on a Cholesky decomposition of the covariance matrix, which provides a transparent ordering scheme for contemporaneous relationships among variables.

2.1 Identification of Weather Regimes

This model specifies the evolution of a weather index z_t using the following dynamic structure:

$$z_t = \mu_{0,\tau_0}(1 - s_t) + \mu_{1,\tau_1}s_t + e_t, \quad (1)$$

where $s_t \in \{0, 1\}$ is a latent binary variable, representing two distinct weather regimes. Specifically, $s_t = 0$ indicates a stable weather regime, and $s_t = 1$ indicates an anomalous regime. The error term e_t follows a white noise process with a normal distribution:²

$$e_t \sim \mathcal{N}(0, \sigma_e^2). \quad (2)$$

The latent state variable s_t evolves according to a two-state Markov chain, similar to [Hamilton \(1989\)](#), where the transition probabilities are defined as:

$$\Pr(s_t = j \mid s_{t-1} = i, s_{t-2} = h, \dots) = \Pr(s_t = j \mid s_{t-1} = i) = p_{ij} \quad (3)$$

The entire sample periods $t = 1, \dots, T$, alternate between N_0 stable weather regimes and N_1 anomalous weather regimes. Importantly, each weather regime has its own mean level: μ_{0,τ_0} for stable weather and μ_{1,τ_1} for anomalous weather. That is, the mean μ_{0,τ_0} represents the expected value of z_t during the τ_0 -th stable weather phase, while μ_{1,τ_1} corresponds to the expected value of z_t during the τ_1 -th anomalous weather.

The flexibility from changing means is particularly relevant in the context of climate

²In the baseline specification, weather regimes affect only the mean of the climate index, while its variance is assumed to remain constant across regimes. This modeling choice is deliberate. Because the climate index aggregates multiple weather-related components within a multivariate framework, allowing both the mean and the variance to vary across regimes could complicate regime interpretation and raise identification issues, including potential label switching, if different components were to exhibit heterogeneous regime dynamics. For instance, rainfall anomalies could display low mean but high volatility in a given period, while wind-related indicators exhibit both low mean and low volatility, making the definition of a common regime ambiguous. Conditioning regime changes on the mean of the aggregate index ensures a coherent classification of stable and anomalous weather periods across all underlying components. Extending the framework to accommodate regime-dependent volatility is a natural avenue for future research.

change, as it allows the average level of the weather index to change over time. In contrast, a standard Markov-switching regression, which has two fixed averages for the two regimes, would not capture this time-varying behavior. As a result, it would be limited in its ability to accurately reflect the changing patterns of climate. As shown in [Baumeister et al. \(2021\)](#), when conditioning on $\{s_t\}_{t=1}^{t=T}$, τ_1 and τ_0 can be represented as time-dependent functions, given by:

$$\begin{aligned}\tau_{1,t} &= \begin{cases} s_1 & , \text{ If } t = 1 \\ s_1 + \sum_{j=2}^t \max(0, s_j - s_{j-1}) & , \text{ Otherwise} \end{cases} \\ \tau_{0,t} &= \begin{cases} 1 - s_1 & , \text{ If } t = 1 \\ (1 - s_1) + \sum_{j=2}^t \max(0, s_{j-1} - s_j) & , \text{ Otherwise} \end{cases}\end{aligned}\quad (4)$$

While the regime-specific means μ_{0,τ_0} and μ_{1,τ_1} depend on the prevailing state s_t , the model imposes a common prior across all recession means and a separate prior for expansion means. During estimation, these priors are refined into posterior distributions unique to each regime, ensuring that the means reflect the characteristics of individual weather phases.

To illustrate the model's behavior, consider situation where $s_t = 0$ (stable weather). In this case, the weather index z_t reflects the stable-weather specific mean μ_{0,τ_0} , while the anomalous weather mean μ_{1,τ_1} is inactive (multiplied by zero) and can be interpreted as a counterfactual. Conversely, when the weather shifts to anomalous ($s_t = 1$), the anomalous weather mean μ_{1,τ_1} governs the dynamics, and the stable weather has no effect. In other words, the model assumes that z_t takes the same value as the τ_1 th anomalous weather phase immediately preceding the τ_0 th stable weather phase. Once the τ_0 th stable weather phase ends, the stable-weather-specific mean μ_{0,τ_0} no longer influences z_t , as $\mu_{0,\tau_0}(1 - s_t) = 0$ according to equation (1). At this point, a new anomalous-weather-specific mean μ_{1,τ_1+1} determines the value of z_t .

The temporal dynamics of the regime-dependent are:

$$\mu_{0,t} = (1 - d_{0,t}) \mu_{0,t-1} + d_{0,t} \mu_{0,\tau_0} \quad (5)$$

$$\mu_{1,t} = (1 - d_{1,t}) \mu_{1,t-1} + d_{1,t} \mu_{1,\tau_1} \quad (6)$$

where the indicator variables $d_{0,t}$ and $d_{1,t}$ are functions of the current and previous regimes and take the following forms:

$$d_{0,t} = \begin{cases} 1 & \text{when } s_t = 0, s_{t-1} = 1, \\ 0 & \text{otherwise.} \end{cases}$$

And

$$d_{1,t} = \begin{cases} 1 & \text{when } s_t = 1, s_{t-1} = 0, \\ 0 & \text{otherwise} \end{cases}$$

The previous structure ensures that the means $\mu_{0,t}$ and $\mu_{1,t}$ adjust at regime-switching points, but remain constant within each phase. Unlike previous models where regime-dependent means follow a random walk (see [Eo and Kim, 2016](#)) the time-varying means needed for the Hamilton filter to calculate the probability of being in regime 1 or 0 (see [Kim and Nelson, 2017](#)), this approach assumes independence of means between weather phases, and such independence allows for greater flexibility in fitting extreme or irregular patterns as noted in [Baumeister et al. \(2024\)](#).

2.2 Structural Vector Autoregression (SVAR)

The regime-dependent SVAR model with exogenous variables and regime-specific shocks is specified as:

$$y_t = \Phi_0 y_{t-1} (1 - D_t) + \Phi_1 y_{t-1} D_t + \Gamma_1 x_t + u_t, \quad (7)$$

where:

- y_t is a vector of **endogenous variables**, including the weather index and relevant economic variables,

- x_t is a vector of **exogenous variables** that are not influenced by the system dynamics but affect the endogenous variables,
- Φ_0 represents the coefficients of lagged endogenous variables during the **stable weather regime** ($D_t = 0$),
- Φ_1 represents the coefficients of lagged endogenous variables during the **anomalous weather regime** ($D_t = 1$),
- Γ_1 is the matrix of coefficients associated with the exogenous variables x_t . Note that, x_t affects the system of equations in both regimes but does not vary with the dummy variable D_t ,
- D_t is a dummy variable that determines the regime:

$$D_t = \begin{cases} 1, & \text{if the regime corresponds to anomalous weather,} \\ 0, & \text{if the regime corresponds to stable weather.} \end{cases} \quad (8)$$

- $u_{0,t}$ and $u_{1,t}$ are vectors of **regime-specific structural shocks** with covariance matrices Σ_0 and Σ_1 , respectively.

In this formulation, the regime dummy D_t ensures that the coefficients of the lagged endogenous variables (Φ_0, Φ_1) depend on the prevailing weather regime.

2.2.1 Identification Strategy

I apply the Cholesky decomposition to the covariance matrix Σ_t of the residuals to identify structural shocks. Specifically:

$$\Sigma_t = P_t P_t', \quad (9)$$

where P_t is a lower triangular matrix. The Cholesky decomposition imposes a recursive structure that orthogonalizes the structural shocks. The ordering of the variables in the vector y_t determines the contemporaneous relationships among them.

2.2.2 Endogenous Variables

The vector y_t includes the weather index and a set of economic variables to capture the dynamic interactions between weather regimes and macroeconomic outcomes. The causal order will be presented in subsection 3.2 while I introduce the endogenous variables.

2.2.3 Estimation

The VAR model is estimated by maximum likelihood, which provides consistent estimates of both the autoregressive coefficients and the covariance matrix of the reduced-form residuals. To identify structural shocks, a Cholesky decomposition is applied to the estimated covariance matrix. This approach imposes a recursive causal ordering by factorizing the matrix into a lower triangular form, allowing the residuals to be expressed as linear combinations of orthogonal structural innovations. The ordering of the variables determines the contemporaneous impact structure.

2.2.4 Impulse Response Analysis

Once the model is estimated, I compute Impulse Response Functions (IRFs) to analyze the dynamic effects of structural shocks on the system. IRFs are calculated separately for each regime, reflecting differences in the responses of the weather index under stable and anomalous weather conditions. This approach allows me to assess how the propagation of weather shocks varies across regimes.

3 Data

3.1 Weather Variables

I construct a climate index by combining five variables using Principal Component Analysis (PCA). This approach is conceptually similar to the Actuaries Climate Index for the United States of the [American Academy of Actuaries and Canadian Institute of Actuaries and Casualty Actuarial Society and Society of Actuaries](#) (2020), which aims to create an aggregate measure by synthesizing individual weather-related series into a single index. While the climate index presented below is inspired by the Actuaries Climate Index, it differs in several respects. The ACI covers a more extended baseline period (starting in 1961) and aggregates six variables using standardized deviations from the 1961–1990 reference. By contrast, my sample is shorter (1985–2024) and relies on five variables, since high-frequency wind and sea level data for Mexico are not easily accessible—often restricted to naval records with limited coverage. Instead of equal weighting, I use Principal Component Analysis (PCA), which endogenously assigns weights based on the common variance across series, allowing the index to capture the shared dynamics of Mexican climate anomalies more effectively.

Figure 2 presents the time series for each variable over their common time frame, spanning from January 1985 to September of 2024.

1. **El Niño:** The El Niño variable is derived from the MENS0 index (Multivariate ENSO Index). It equals the MENS0 index value when it is greater than zero and is set to zero otherwise, effectively isolating the positive phases of the MENS0 index that correspond to El Niño events. The MENS0 index measures sea surface temperature anomalies and other meteorological indicators.³

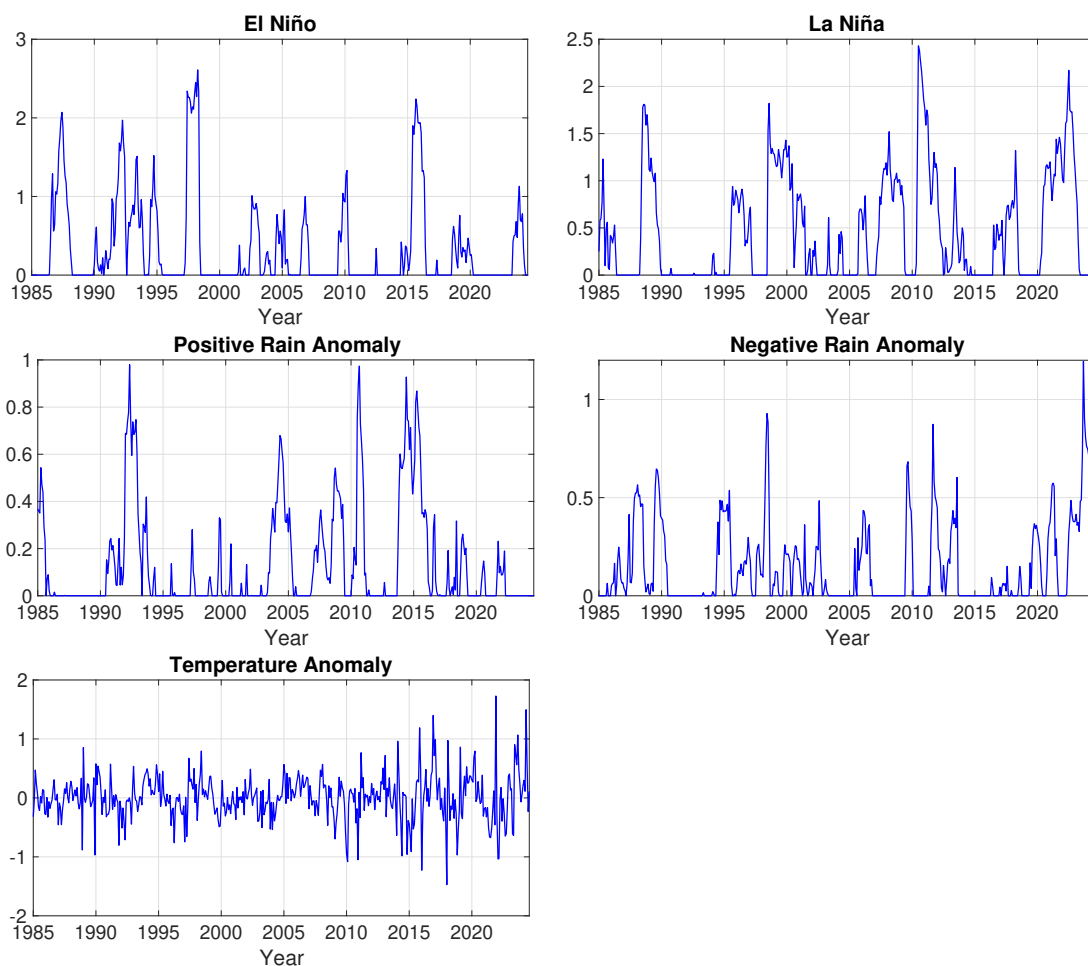
³The Multivariate ENSO Index (MENS0), developed by NOAA, combines six key meteorological and oceanographic variables to monitor the El Niño-Southern Oscillation (ENSO) phases: sea-level pressure, zonal and meridional surface winds, sea surface temperature, surface air temperature, and total cloudiness. Positive MENS0 values indicate El Niño conditions, while negative values reflect La Niña events. For more information, refer to [National Oceanic and Atmospheric Administration \(NOAA\)](#) (2024).

2. **La Niña:** Similarly, I calculate the La Niña variable from the MENS index. It equals the MENS value when it is less than zero and is zero otherwise, capturing the negative phases associated with La Niña events.
3. **Positive Rain Anomaly:** This variable is calculated using the SP12 index, which measures Standardized Precipitation over a 12-month scale. The SP12 reflects deviations in precipitation from historical averages. For this variable, I take the absolute value of SP12 but set it to zero when SP12 is less than zero, focusing on months with above-average precipitation. The data is sourced from the National Water Commission of Mexico ([Comisión Nacional del Agua \(CONAGUA\), 2024](#)).
4. **Negative Rain Anomaly:** This variable is also derived from the SP12 index. It equals the absolute value of SP12 but is set to zero when SP12 is greater than zero, concentrating on months with below-average precipitation from the previous 12 months. This data is obtained from [Comisión Nacional del Agua \(CONAGUA\) \(2024\)](#).⁴
5. **Temperature Anomaly:** I calculate the temperature variable by subtracting a 60-month moving average from the monthly average temperature. This approach aims to identify deviations from long-term temperature trends. The data is sourced from [Comisión Nacional del Agua \(CONAGUA\) \(2024\)](#).⁵

⁴While positive and negative rainfall anomalies are mechanically related, I distinguish between them to capture potentially asymmetric effects. Above-average precipitation may be associated with flooding or infrastructure disruptions, whereas below-average precipitation often reflects drought conditions. These distinct weather phenomena can influence inflation through different channels, such as supply chain disruptions or agricultural yield reductions, as documented in the literature, e.g. by [Dell et al. \(2012\)](#).

⁵I use a 60-month moving average to capture medium-term temperature trends. This window length was chosen at my discretion, as it strikes a balance between smoothing short-term fluctuations and retaining sufficient variability in the data. Unlike other studies, such as [Kim et al. \(2024\)](#), which use reference periods starting in the 1960s, my dataset does not extend that far back, limiting the feasibility of adopting a more extended historical baseline. I acknowledge this as a limitation; however, the chosen horizon still allows for the meaningful identification of temperature anomalies over time.

Figure 2: Component Variables of the Weather Index



Notes. The figure displays the standardized variables that comprise the weather index. The first variable represents the component of the MENS index associated with El Niño, while the second corresponds to La Niña. The third graph shows positive rainfall anomalies over the past 12 months, and the fourth illustrates negative rainfall anomalies for the same period. The final graph depicts temperature anomalies relative to a 60-month moving average.

Source: ([Comisión Nacional del Agua \(CONAGUA\), 2024](#)) and [National Oceanic and Atmospheric Administration \(NOAA\) \(2024\)](#).

3.1.1 Standardization and Aggregation

I standardize all variables to ensure comparability. Standardization transforms each variable into a z-score by subtracting its mean and dividing by its standard deviation, effectively eliminating differences in units and scales.

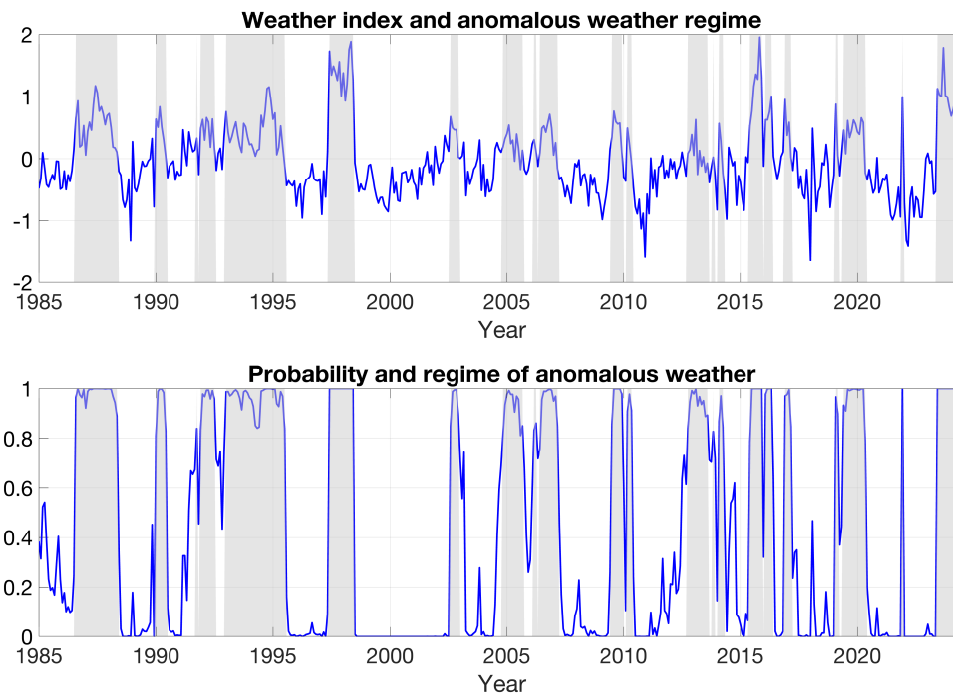
After standardization, I apply PCA to consolidate the variables into a single index. The first principal component serves as the climate index, summarizing the shared variance across the standardized variables. The explained variance of the first component is 41.7%. Figure 3 (top graph) presents the climate index and the anomalous weather regimes. The top panel displays the climate index alongside the regimes identified using the methodology described in subsection 2.1, with shaded regions indicating periods of anomalous weather. The bottom panel illustrates the probability of anomalous weather over time. From the mid-2020s onward, the frequency of anomalous weather increases, as evidenced by the expanded shaded regions and higher probabilities. This rise can be attributed to a greater prevalence of La Niña events, negative rain anomalies, and temperature anomalies, as shown in Figure 2.⁶

3.1.2 Estimation

I estimate the model presented in subsection 2.1 using Bayesian techniques, assuming normal priors for $\tau_{1,t}$ and $\tau_{0,t}$, Beta distributions for the regime probabilities p_{ij} , and a Gamma distribution for σ_e^2 . For inference on s_t , I apply a modified version of the Carter and Kohn (1994) algorithm, as implemented by Kim and Nelson (2017). To ensure convergence and reliable results, I ran 12,000 iterations of the Metropolis-within-Gibbs sampler, discarding the initial 2,000 as burn-in. For a detailed explanation of the algorithm, see Baumeister et al.

⁶While using PCA to construct a composite weather index may obscure the individual effects of specific variables, I view the aggregate response as an interesting result in itself. As shown in Section 4, weather anomalies can influence the economy through heterogeneous channels—such as droughts, floods, heatwaves, or unseasonal frosts—each affecting different sectors and regions. That the combined index produces statistically significant effects at the aggregate level suggests that these diverse shocks, despite their localized nature, may collectively shape national inflation dynamics. This supports the relevance of incorporating a summary weather measure in macroeconomic analysis.

Figure 3: Weather Index and Probability of Belonging to an Anomalous Regime



Notes. The top graph displays the composite weather index constructed using the variables described in subsection 3.1. The bottom graph shows the probability of belonging to the anomalous weather regime, estimated using the regime-switching model with time-varying means from subsection 2.1. In both graphs, the shaded areas indicate periods classified as part of the anomalous weather regime.

(2021) and [Baumeister et al. \(2024\)](#).

The estimation procedure yields, for each period in the sample, the probability of being in a stable regime—when the conditional mean of the weather index is relatively low—or in an anomalous regime—when the mean is relatively high. These probabilities, illustrated in Figure 3 (bottom graph), provide a data-driven identification of weather phases. This regime classification will later serve as an input for the SVAR model, allowing the effects of weather shocks on inflation to be estimated under stable and anomalous conditions.

3.2 Endogenous Economic Variables

This section introduces the endogenous variables used in the analysis: the weather index, the Global Economic Activity Index (IGAE), the unemployment rate, headline, core and non-core inflation, the exchange rate and interest rates. Figure 3 displays these variables over the common time frame from January 2005 to September 2024.

The first plot reproduces the weather index introduced in earlier sections. The second graph presents the IGAE, as monthly percentage changes, using the seasonally adjusted series published by [Instituto Nacional de Estadística y Geografía \(2024b\)](#). The third graph depicts the monthly change in Mexico’s seasonally adjusted unemployment rate, with data sourced from [Instituto Nacional de Estadística y Geografía \(2024a\)](#).

The fourth, fifth, and sixth graphs show monthly percentage changes in headline, core, and non-core inflation, respectively, calculated from deseasonalized data. Deseasonalization is performed using the X-13ARIMA-SEATS method developed by the [U.S. Census Bureau \(2017\)](#), with the original data sourced from [Instituto Nacional de Estadística y Geografía \(2025\)](#).

The bottom two graphs focus on financial variables. The second-to-last graph illustrates the monthly change in the exchange rate, with data obtained from [Banco de México \(2024\)](#). The final graph shows the monthly change in the 28-day CETES, which are short-term gov-

ernment securities issued by the Mexican Treasury. These securities serve as a benchmark for interest rates. Data for CETES also comes from [Banco de México \(2024\)](#).

Finally, I conducted the Augmented test of [Dickey and Fuller \(1979\)](#) (ADF) to ensure the stationarity of all variables and confirmed that the transformations render them suitable for the analysis.

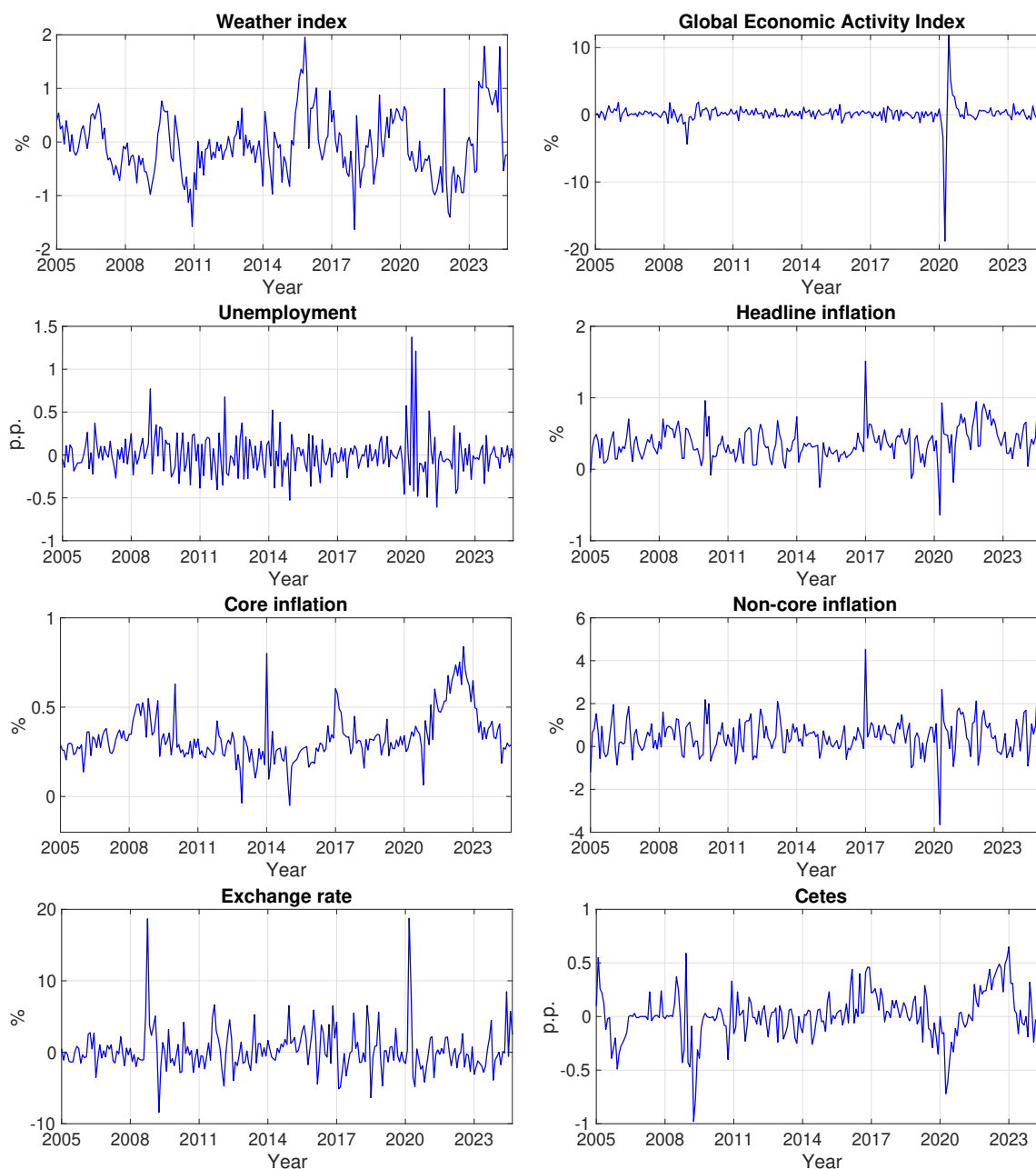
The causal order for the SVAR model is determined as follows: the weather index, the IGAE, the change in the unemployment rate, inflation, and changes in the exchange rate and interest rates. This ordering aligns with the approach used by [Kim et al. \(2024\)](#) and implies that the contemporaneous relationships among the variables are structured based on this sequence using the Cholesky decomposition. Specifically, the weather index contemporaneously influences all other variables, reflecting its role as an exogenous factor. The IGAE impacts the unemployment rate, inflation, exchange rate, and interest rates but does not contemporaneously respond to these variables. Similarly, the change in the unemployment rate affects inflation, exchange rate, and interest rates without contemporaneous feedback from them. Inflation influences the exchange rate and interest rates, while the exchange rate contemporaneously impacts interest rates but not vice versa.

3.3 Exogenous Economic Variables

In the SVAR specification, the dummy variables D_t correspond to the weather regimes identified in subsection [3.1.2](#). Specifically, $D_t = 0$ indicates periods classified as stable, while $D_t = 1$ corresponds to anomalous regimes.

Figure [5](#) displays the exogenous variables. The first panel shows the Global Supply Chain Pressure Index (GSCPI), developed by the [Federal Reserve Bank of New York \(2024\)](#). This index combines global transportation costs and supply chain pressure data, utilizing a principal component analysis (PCA) methodology to capture common disruptions across supply chain indicators. Its goal is to provide a quantitative measure of global supply chain stress,

Figure 4: Endogenous Variables Included in the SVAR Model



Notes. The graphs display the variables included in the SVAR model, presented in the same causal order as used in the Cholesky decomposition.

Source: [Instituto Nacional de Estadística y Geografía \(2024a\)](#) and [Banco de México \(2024\)](#).

reflecting the intensity of logistical bottlenecks and their global impact.

The second panel presents the monthly change in the Commodity Price Index of the [World Bank \(2024\)](#), which aggregates prices of various commodities into a single index. The methodology accounts for both energy and non-energy commodity prices, weighted by their global trade importance. This index aims to track global commodity price movements, providing insights into the volatility and trends that can influence economic outcomes.

The third panel shows the monthly change in U.S. Industrial Production, sourced from [Federal Reserve Bank of St. Louis \(2024\)](#). This variable reflects changes in the output of the manufacturing, mining, and utilities sectors in the United States and serves as a proxy for domestic economic activity.

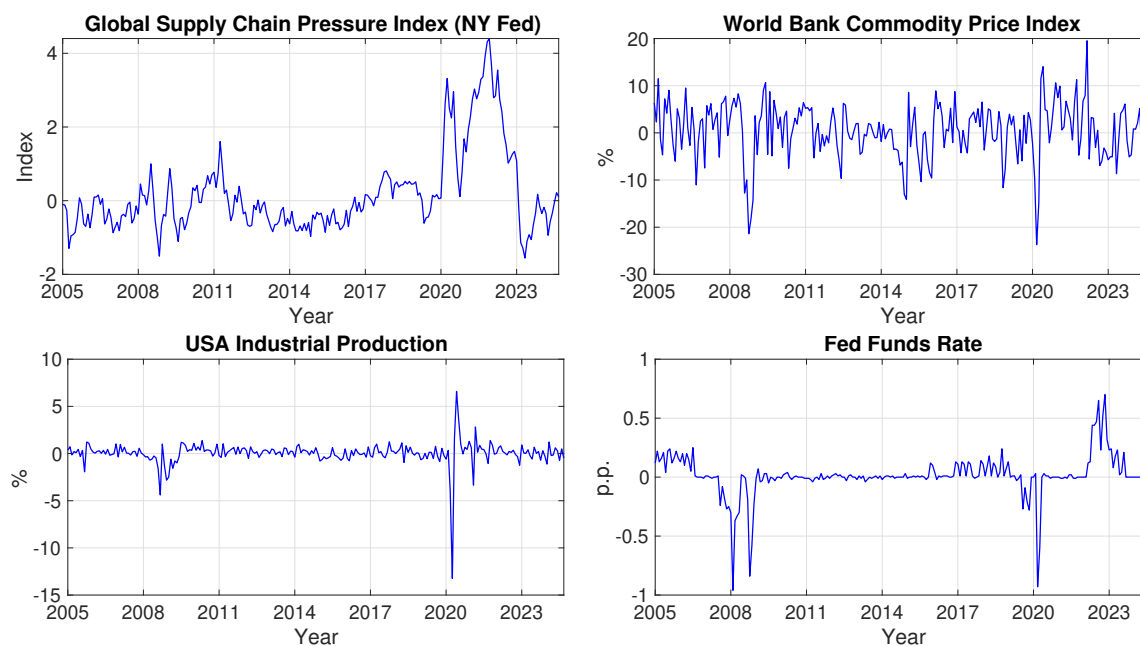
Finally, the last panel depicts the Federal Funds Rate sourced from FRED. For periods when the Federal Funds Rate approached the zero lower bound, I adjusted the series using the shadow rate methodology of [Wu and Xia \(2016\)](#) which estimates the effective monetary policy stance during unconventional monetary policy interventions. As with the endogenous variables, I checked for stationarity using the ADF test.

3.4 Stationarity tests for the endogenous and exogenous variables

I assess the time-series properties of both the endogenous (Y) and exogenous (X) variables by applying standard unit root and stationarity tests. Specifically, I use the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests, for which the null hypothesis is the presence of a unit root (non-stationarity), as well as the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, for which the null hypothesis is stationarity around a constant. As general references, I follow [Hamilton \(2020\)](#) and [Enders \(2008\)](#). I present the results in Table 1.

The results indicate that most of the endogenous variables (Y) are stationary at conventional significance levels. The weather index, global economic activity, unemployment, headline and non-core inflation, the exchange rate, and Cetes generally reject the unit root null in

Figure 5: Exogenous Variables Included in the SVAR Model



Notes. The graph displays the exogenous variables incorporated into the SVAR model.

Source: [Federal Reserve Bank of New York \(2024\)](#), [World Bank \(2024\)](#) and [Federal Reserve Bank of St. Louis \(2024\)](#).

Variable	ADF (ARD)	ADF (TS)	PP	KPSS (c)
<i>Panel A: Endogenous variables (Y)</i>				
Weather index	0.009	0.043	0.001	NR
Global Economic Activity Index	0.001	0.001	0.001	NR
Unemployment	0.005	0.012	0.001	NR
Headline inflation	0.022	0.076	0.001	NR
Core inflation	0.092	0.238	0.013	NR
Non-core inflation	0.001	0.005	0.001	NR
Exchange rate	0.001	0.002	0.001	NR
Cetes	0.029	0.116	0.001	NR
<i>Panel B: Exogenous variables (X)</i>				
GSCPI (NY Fed)	0.105	0.158	0.005	NR
Commodity Price Index (WB)	0.005	0.022	0.001	NR
USA Industrial Production	0.003	0.013	0.001	NR
Fed Funds Rate	0.012	0.020	0.001	NR

Notes: Values in columns report p-values. “NR” means that the KPSS test does not reject the null hypothesis of stationarity. ADF (Augmented Dickey-Fuller, ARD = constant, TS = constant and trend) and PP (Phillips-Perron) tests have the null hypothesis of a **unit root** (non-stationarity). The KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test has the null hypothesis of **stationarity** around a constant. Significance level: 5%.

the ADF or PP tests, while the KPSS does not reject stationarity. Core inflation shows the weakest evidence, as the ADF test fails to reject the null, though the PP test suggests stationarity, which is consistent with its high persistence. For the exogenous variables (X), the global supply chain pressure index provides mixed evidence (non-rejection in ADF but rejection in PP), while the commodity price index, U.S. industrial production, and the federal funds rate all display strong support for stationarity. Although some variables do not pass the tests at the 5% level, they do so at the 10% level, which suggests that the issue is not severe. I believe these borderline cases may arise from the COVID-19 episodes, which generated structural breaks and increased inflation persistence. In Section 4, I conduct robustness checks using alternative specifications and demonstrate that the results remain qualitatively unchanged when the models are run on pre-pandemic samples.

4 Results

4.1 Headline Inflation and Weather Shocks

Figure 6 displays the impulse response functions (IRFs) for a one-standard-deviation shock to the weather index during the stable-weather regime. The top panels show the IRFs, while the bottom illustrates the cumulative effects. Among all variables, only headline inflation exhibits a statistically significant response, increasing over time. After 15 months, the accumulated effect on inflation reaches approximately 0.15 percentage points, highlighting the relevance of weather shocks in shaping inflation dynamics.

Figure 7 presents the analogous impulse response functions (IRFs) for the anomalous weather regime ($D_t = 1$). The main finding persists: headline inflation increases significantly in response to weather shocks, with a stronger and more persistent response compared to the stable regime. The cumulative effect reaches nearly 0.2 percentage points after 15 months.

As shown by the remaining variables, economic activity does not exhibit statistically significant responses. This muted effect may stem from the use of aggregate data, where positive outcomes in other regions or sectors may offset localized disruptions. Additionally, heterogeneous climate shocks can generate divergent effects across space and industries, which may cancel out in national-level estimates.

4.2 Core Inflation and Weather Shocks

Figure 8 presents the impulse response functions (IRFs) during the stable weather regime using core inflation instead of headline inflation. The top panel illustrates the IRFs during the stable weather regime, where the results show no significant effects. All IRFs remain near zero and lack statistical significance, indicating that core inflation does not respond to weather shocks. Similarly, while there is a slight decrease in interest rates, this effect is also statistically insignificant.

The bottom panel, which displays the cumulative effects, confirms these findings. The cumulative results are not statistically significant, reinforcing the conclusion that weather shocks do not impact core inflation. This outcome is expected, as core inflation, by design, excludes components like agricultural items and energy prices that are more susceptible to weather-related disruptions. These findings further emphasize the stability of core inflation in the face of weather variability, contrasting with the more pronounced effects observed on headline and non-core inflation. As such, the following subsection examines the effects on the other component of headline inflation: non-core inflation.

Under the anomalous weather regime, Figure 9 reveals notable changes following a shock to the weather index. In contrast to the stable regime, there are small but statistically significant decreases in unemployment, the exchange rate (indicating an appreciation), and interest rates. However, as in the stable weather regime, core inflation does not respond to the shock.

The decline in unemployment may reflect a reallocation of labor in response to the weather shock as workers adjust to changes in economic activity. The appreciation of the exchange rate could be driven by changes in relative prices and external conditions, including temporary movements in trade revenues or capital inflows following climate-related disruptions. The reduction in interest rates likely represents an adjustment in response to the increase in slack and an appreciation of the currency. However, it is important to acknowledge the possibility that model uncertainty may contribute to this result, warranting further research.

4.3 Non-core Inflation and Weather Shocks

Figure 10 presents the IRFs of macroeconomic variables to a one-standard-deviation shock to the weather index during the stable weather regime. Notably, only non-core inflation exhibits a statistically significant response. The bottom panel shows that cumulative non-core inflation increases by approximately 0.2 percentage points around 12 months after the shock, suggesting heightened sensitivity to climate disturbances. In the case of Mexico, this re-

sponse is likely driven primarily by agricultural prices, as energy prices are subject to policy arrangements that mitigate short-term price fluctuations. This contrasts with evidence from other countries, where climate shocks have been found to transmit through energy prices additionally. Other variables, including output and unemployment, do not respond significantly and are therefore interpreted cautiously.

Figure 11 displays the IRFs under the anomalous weather regime. Once again, only non-core inflation shows a significant reaction. While point estimates suggest a lower cumulative effect than in the stable regime, the differences lie within overlapping confidence intervals, indicating no statistically significant difference between regimes.

4.4 Robustness Checks

To assess the robustness of the main results, I implement a series of alternative specifications. These checks include modifications to the ordering of endogenous variables, the exclusion of exogenous controls, and the restriction of the sample to the period prior to the COVID-19 pandemic. The objective is to verify that the qualitative patterns of the impulse response functions (IRFs), particularly the inflationary response to weather shocks, are not driven by specific modeling assumptions.⁷

4.4.1 Alternative Variable Ordering

I change the sequence in which endogenous variables enter the VAR model to test the sensitivity of results to the identification strategy based on Cholesky decomposition in Figure 12. In the baseline specification, economic activity (IGAE) is placed immediately after the weather index, followed by unemployment. In the alternative ordering, unemployment appears di-

⁷Note: In the baseline specification, the ordering of endogenous variables is: weather index, unemployment, economic activity (IGAE), non-core inflation, interest rate, and exchange rate. As a robustness check, I modified this sequence to place economic activity directly after the weather index and unemployment third. The new order is thus: weather index, economic activity, unemployment, non-core inflation, exchange rate, and interest rate.

rectly after the weather index, with IGAE listed next. Despite this change, the qualitative response of inflation remains consistent, indicating that our main findings are not driven by variable ordering.

4.4.2 Threshold VAR with Extreme Weather Regimes

As an additional robustness check, I estimate a threshold VAR model in which the level of the weather index determines the regimes in Figure 13. Specifically, I define two regimes based on whether the weather index is above or below its 80th percentile. Similar to the Markov-Switching method, this approach allows me to assess whether the macroeconomic effects of weather shocks differ significantly when weather conditions are particularly extreme, as opposed to more moderate fluctuations. By focusing on high-percentile thresholds, this specification aims to isolate the nonlinear dynamics that may arise under severe weather stress.

4.4.3 VAR with Only Endogenous Variables

In this study, we re-estimate the Vector Autoregression (VAR) model by excluding external controls, such as global supply chain pressures and commodity prices. The new IRFs are shown in Figure 14. This methodological modification serves to validate that the additional exogenous variables do not influence the estimated response variables. Our findings indicate that the inflation response to weather shocks is preserved.

4.4.4 Pre-COVID-19 Sample Period

To determine if the observed patterns are affected by the significant volatility experienced during and after the COVID-19 pandemic, I limit the analysis to data up until December 2019 in Figure 15. The main findings remain consistent, indicating that the relationship between weather anomalies and inflation existed before the pandemic.

5 Conclusion⁸

This study constructs an aggregate climate index inspired by the Actuaries Climate Index (ACI) and applies a regime-switching approach to classify stable and anomalous weather periods. These regimes are incorporated into a Structural VAR with exogenous variables to estimate the effects of weather shocks on inflation.

The results show that weather shocks positively affect headline and non-core inflation at the national level, particularly during anomalous regimes. In contrast, core inflation remains shielded as expected since it excludes agricultural items and energy. Finding effects on aggregate inflation—rather than only at localized prices—stresses the relevance of these results for the conduct of monetary policy. Since weather shocks increase inflation but do not originate from demand pressures, central bank communication becomes essential: clearly explaining their supply-driven nature helps ensure that, even in the absence of an immediate policy response, inflation expectations remain well anchored.

⁸Disclaimer on use of AI tools: Portions of the MATLAB code used in this study were refined with the assistance of ChatGPT (OpenAI), a large language model, to enhance readability and efficiency. Additionally, I used Grammarly to help me with grammar and spelling corrections in the English language. All modeling decisions, analyses, and interpretations remain my sole responsibility.

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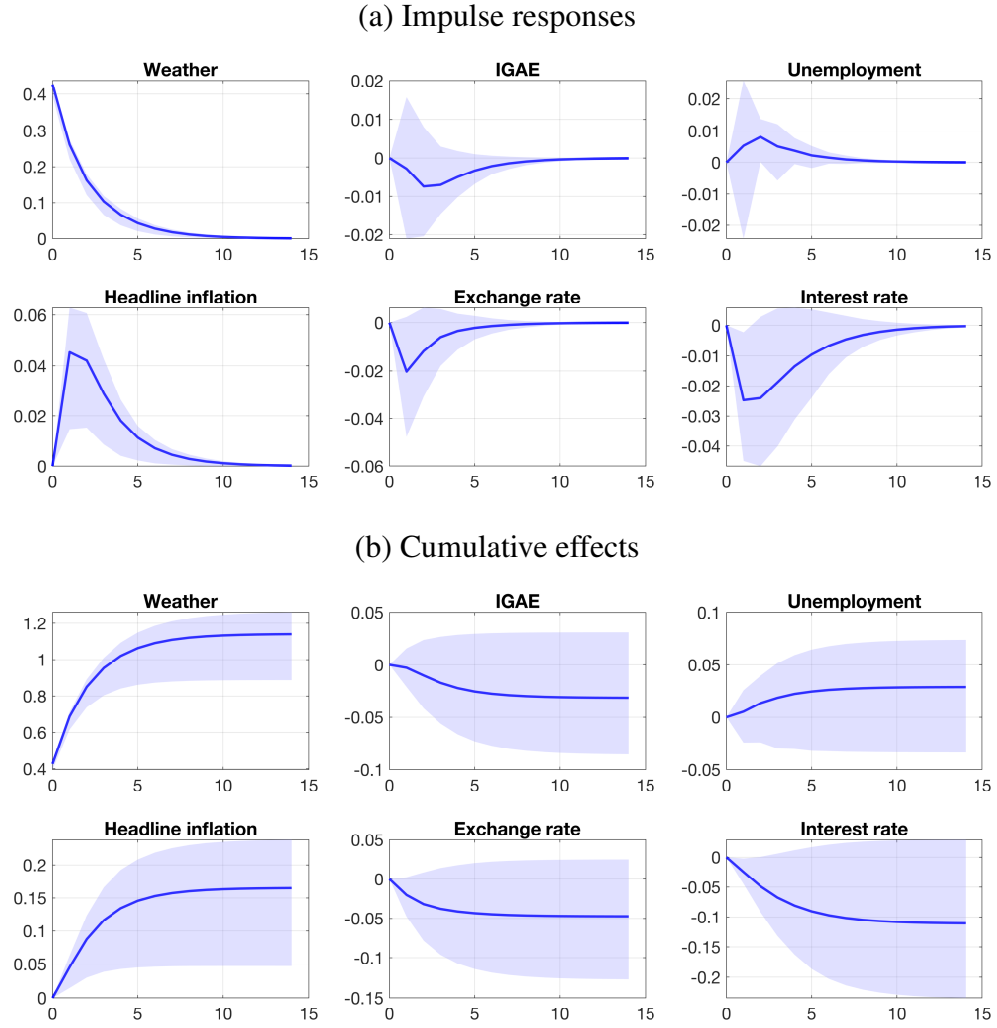
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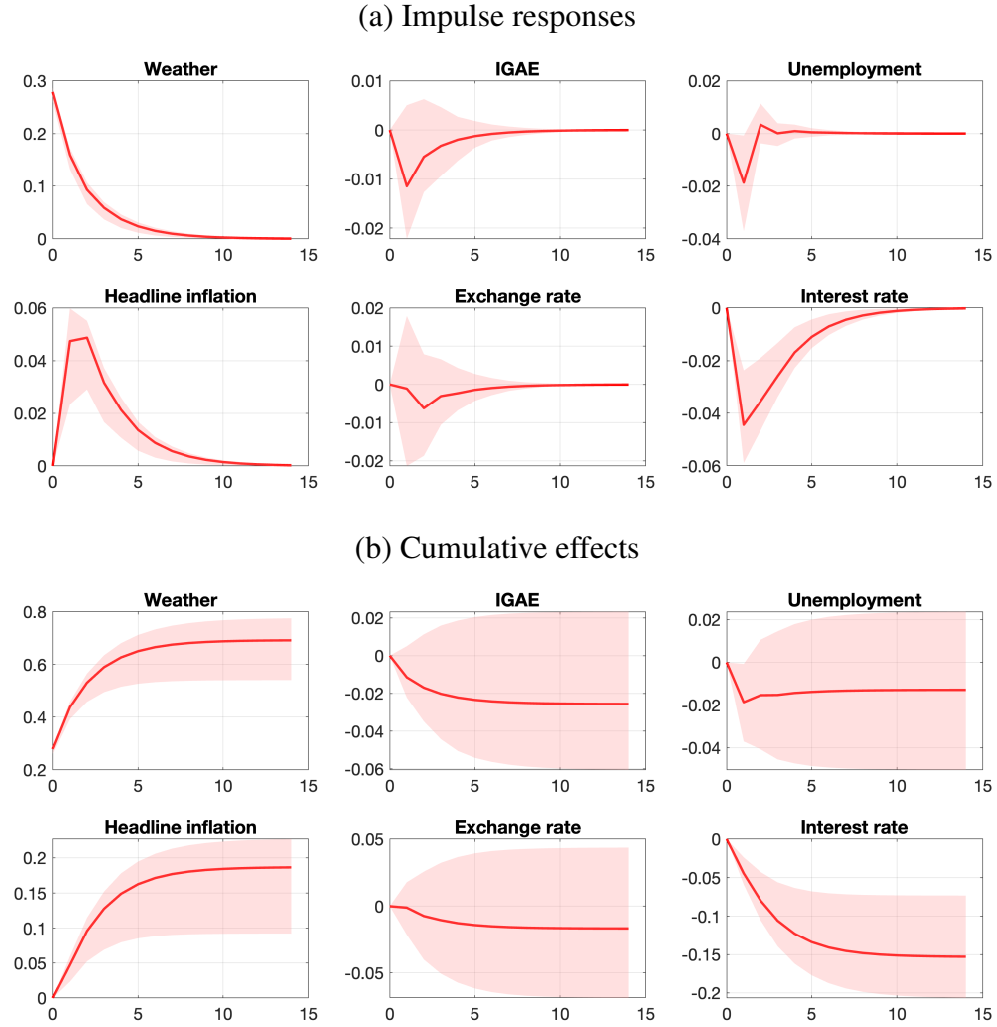
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Figure 6: Impulse Response Functions of Macroeconomic Variables to a One-Standard-Deviation Shock to the Weather Index During the Stable-Weather Regime [Headline Inflation]



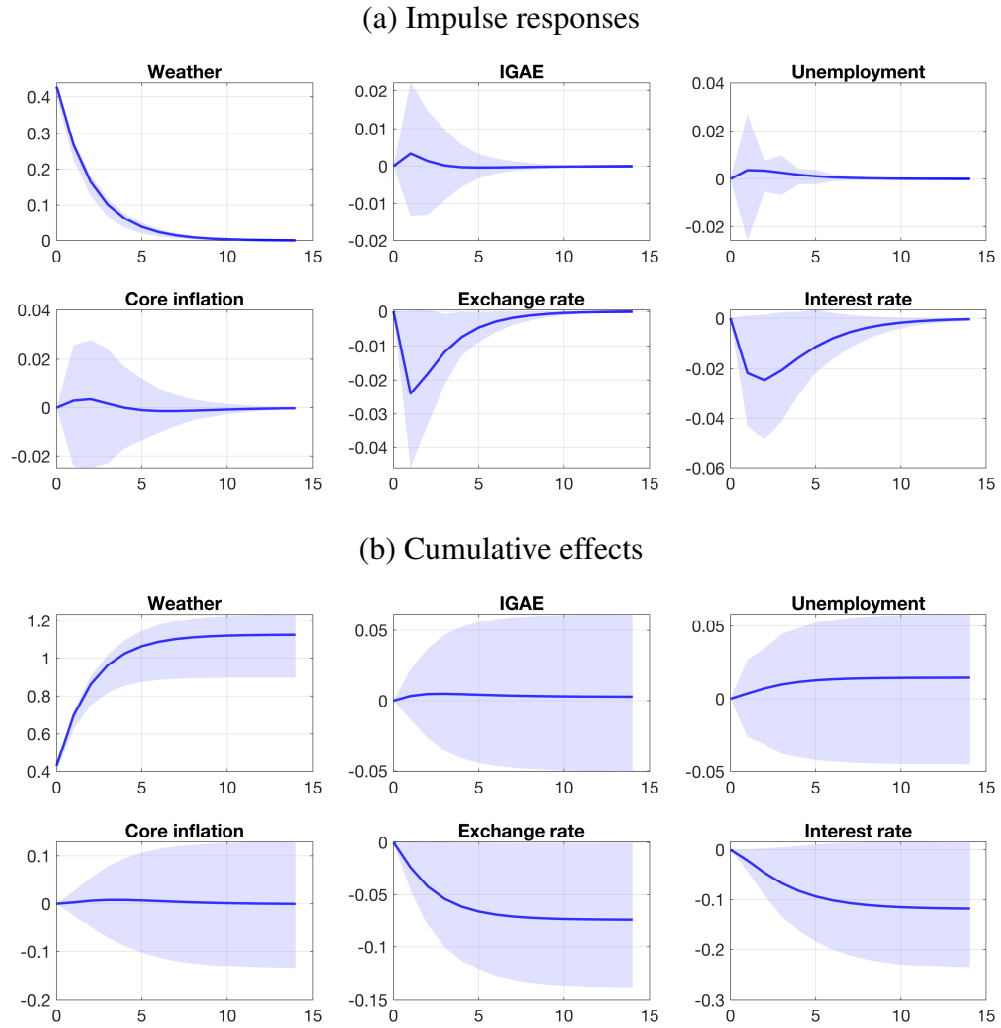
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime $D_t = 0$, with a focus on headline inflation.

Figure 7: Impulse Response Functions of Macroeconomic Variables to a One-Standard-Deviation Shock to the Weather Index During the Anomalous-Weather Regime [Headline Inflation]



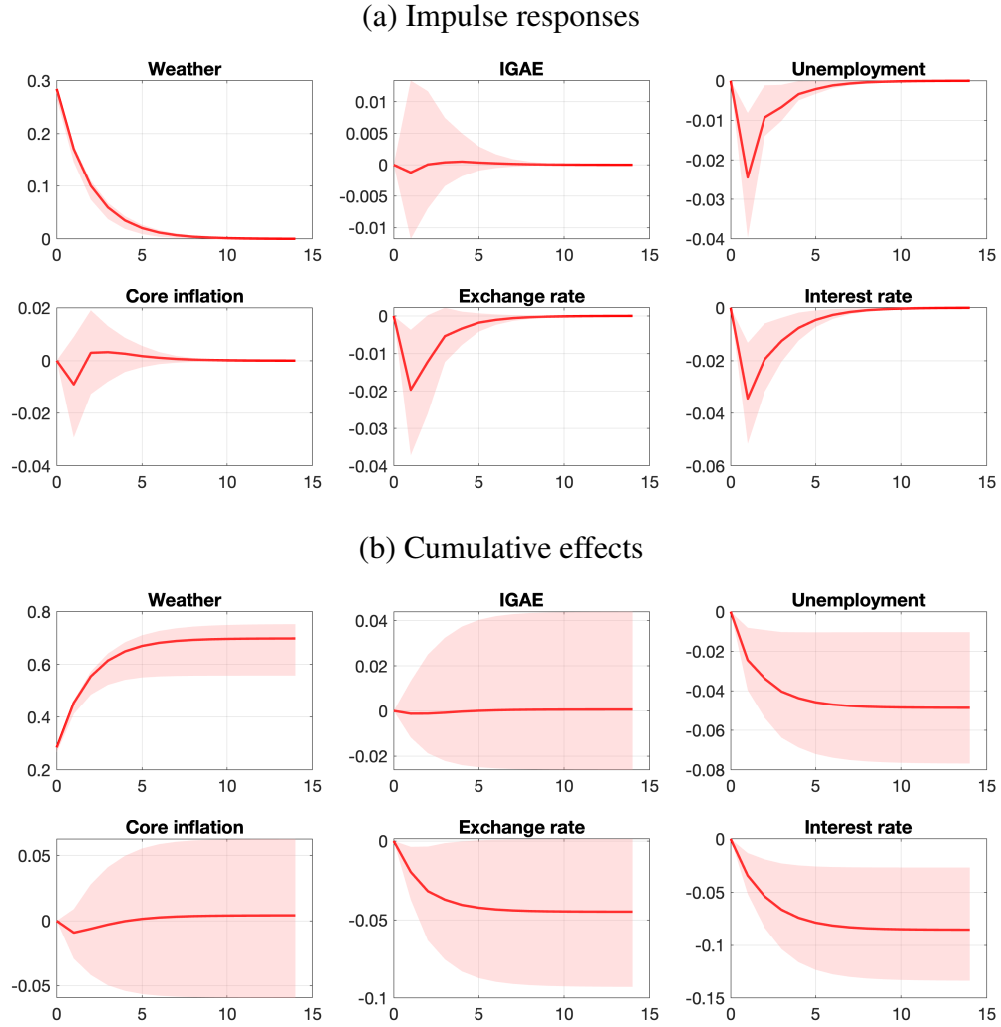
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime $D_t = 1$, with a focus on headline inflation.

Figure 8: Impulse Response Functions (IRFs) of Macroeconomic Variables to a One-Standard-Deviation Shock to the Weather Index During the Stable-Weather Regime [Core Inflation]



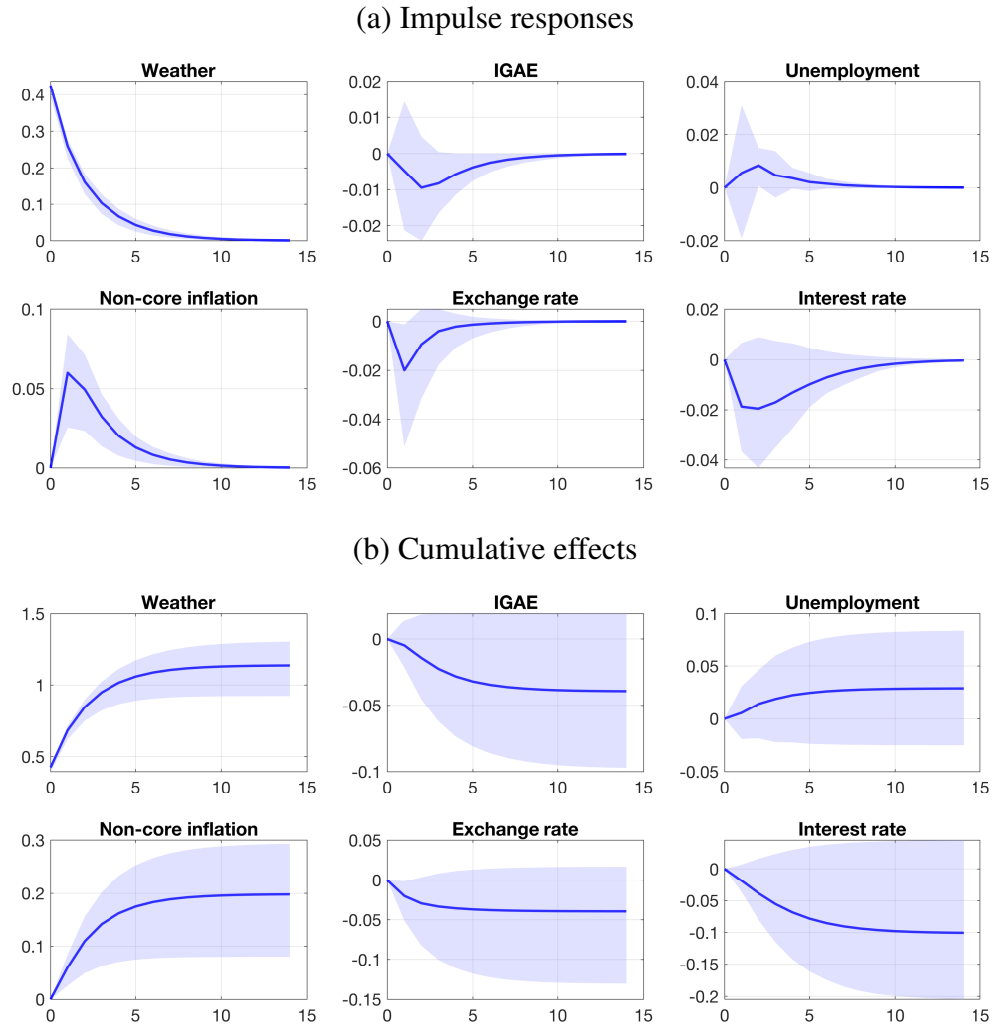
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime $D_t = 0$, with a focus on core inflation.

Figure 9: Impulse Response Functions of Macroeconomic Variables to a One-Standard-Deviation Shock to the Weather Index During the Anomalous-Weather Regime [Core Inflation]



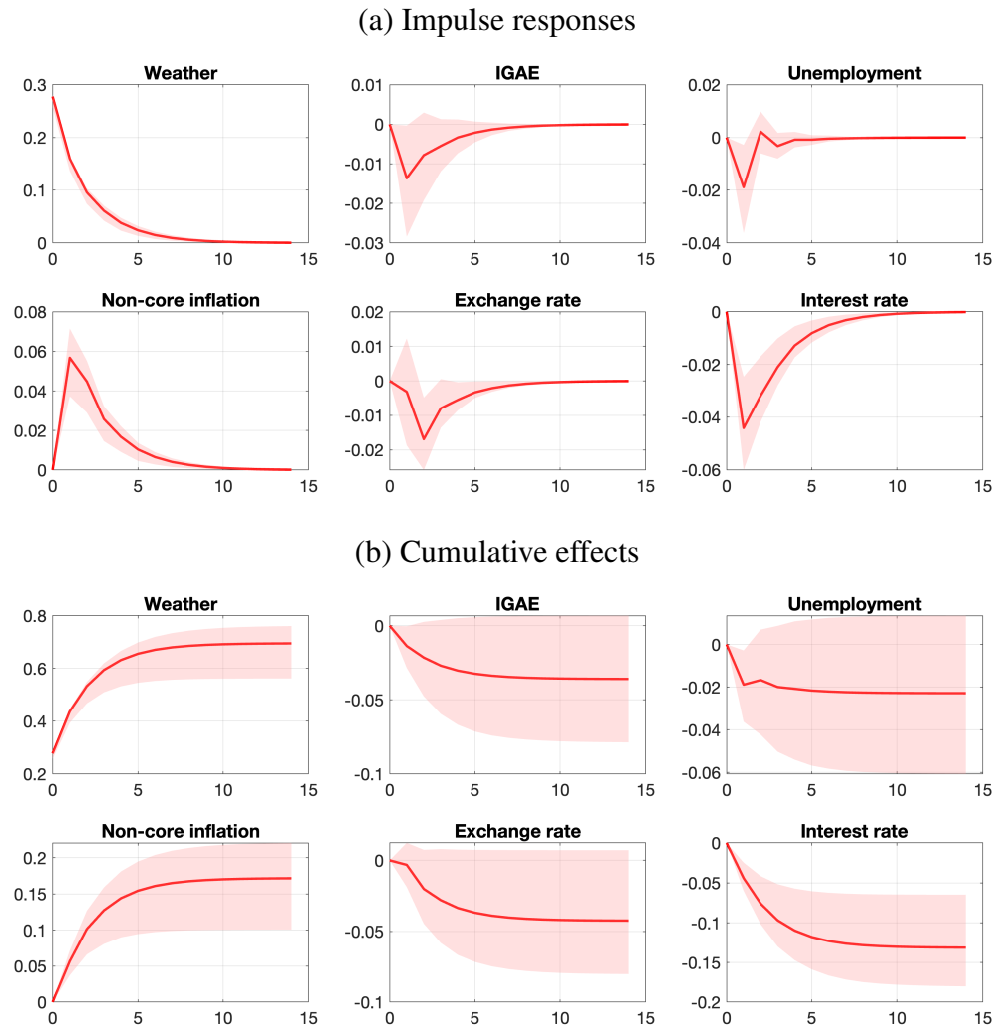
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime $D_t = 1$, with a focus on core inflation.

Figure 10: Impulse Response Functions (IRFs) of Macroeconomic Variables to a One-Standard-Deviation Shock to the Weather Index During the Stable-Weather Regime [Non-core Inflation]



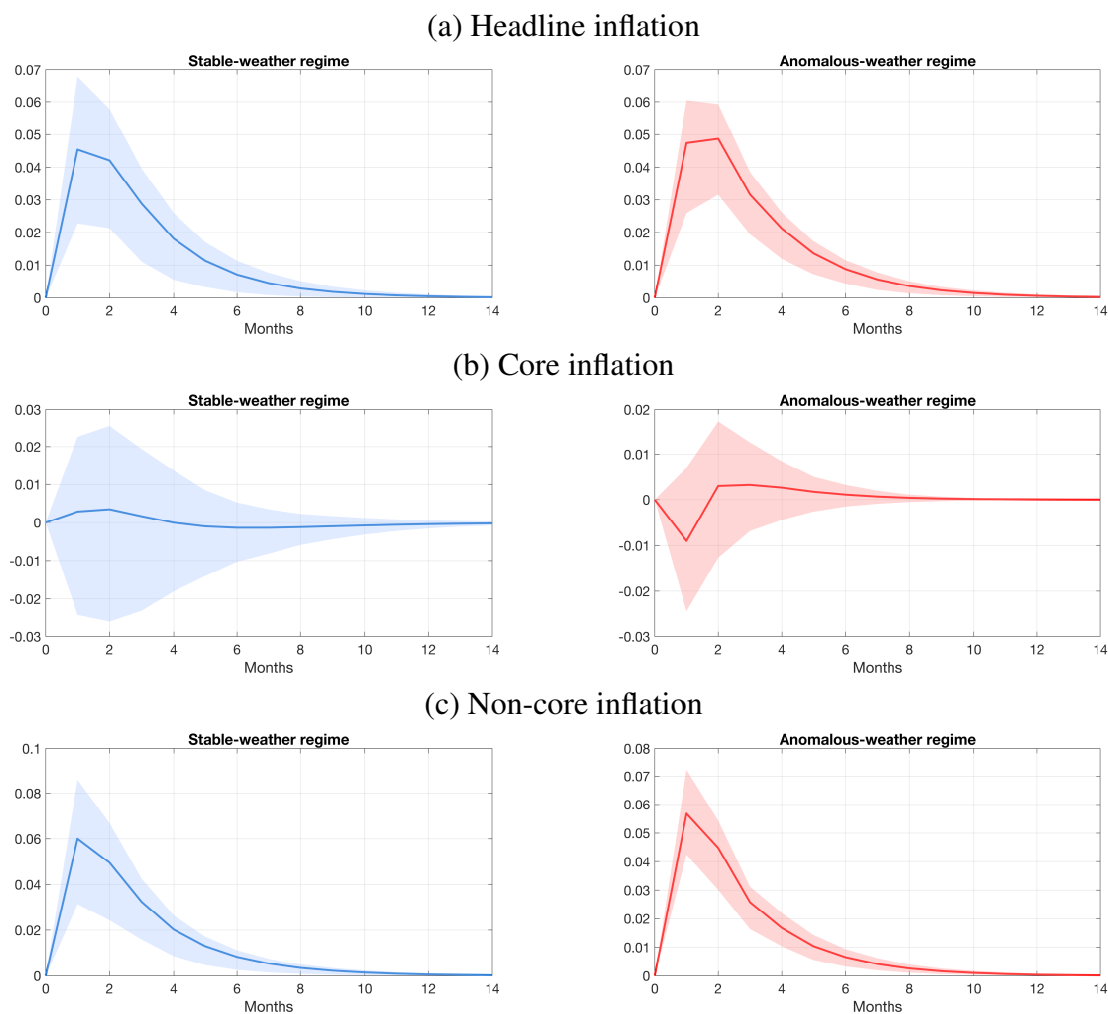
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime $D_t = 0$, with a focus on non-core inflation.

Figure 11: Impulse Response Functions of Macroeconomic Variables to a One-Standard-Deviation Shock to the Weather Index During the Anomalous-Weather Regime [Non-core Inflation]



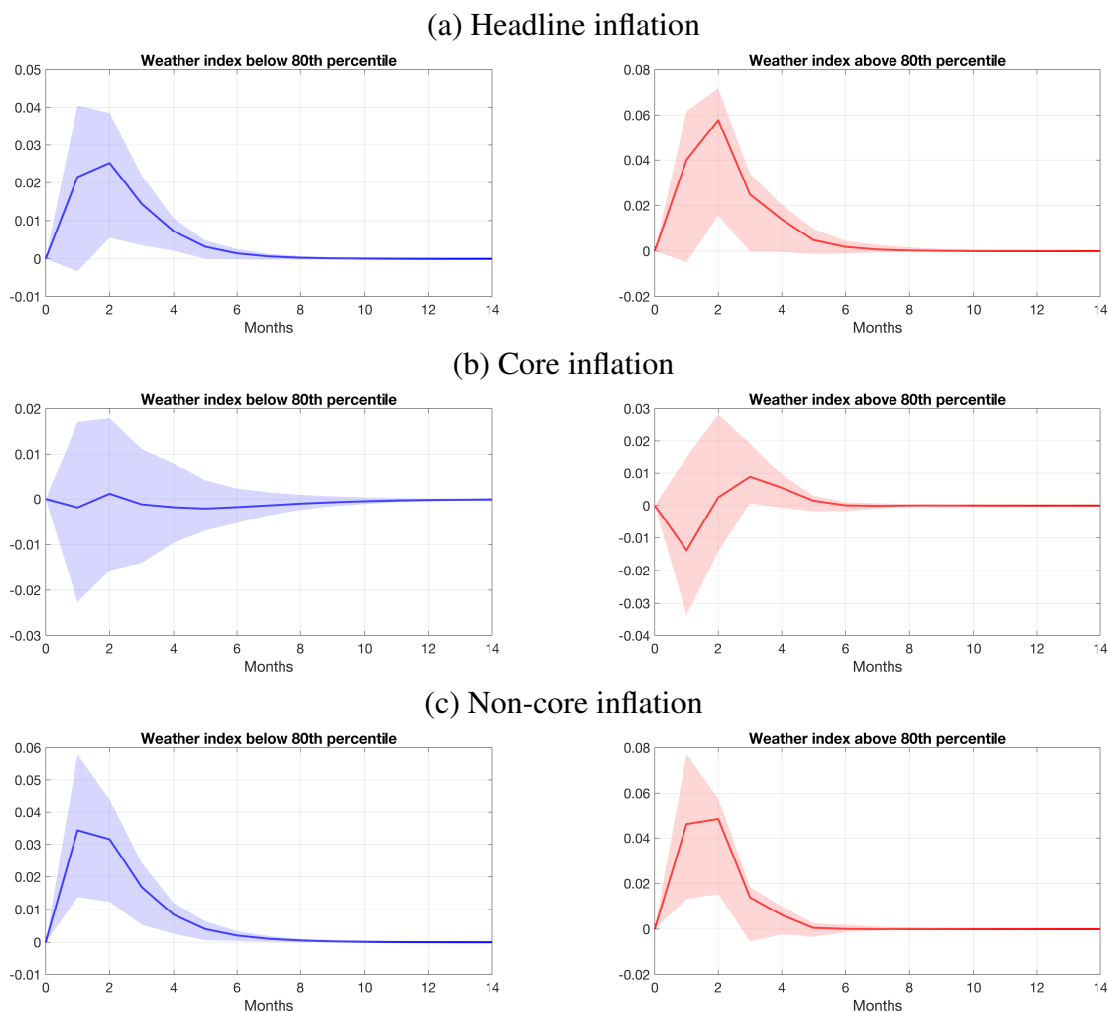
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime $D_t = 1$, with a focus on non-core inflation.

Figure 12: Impulse Response Functions of Inflation Measures to a One-Standard-Deviation Shock to the Weather Index (Alternative Variable Ordering)



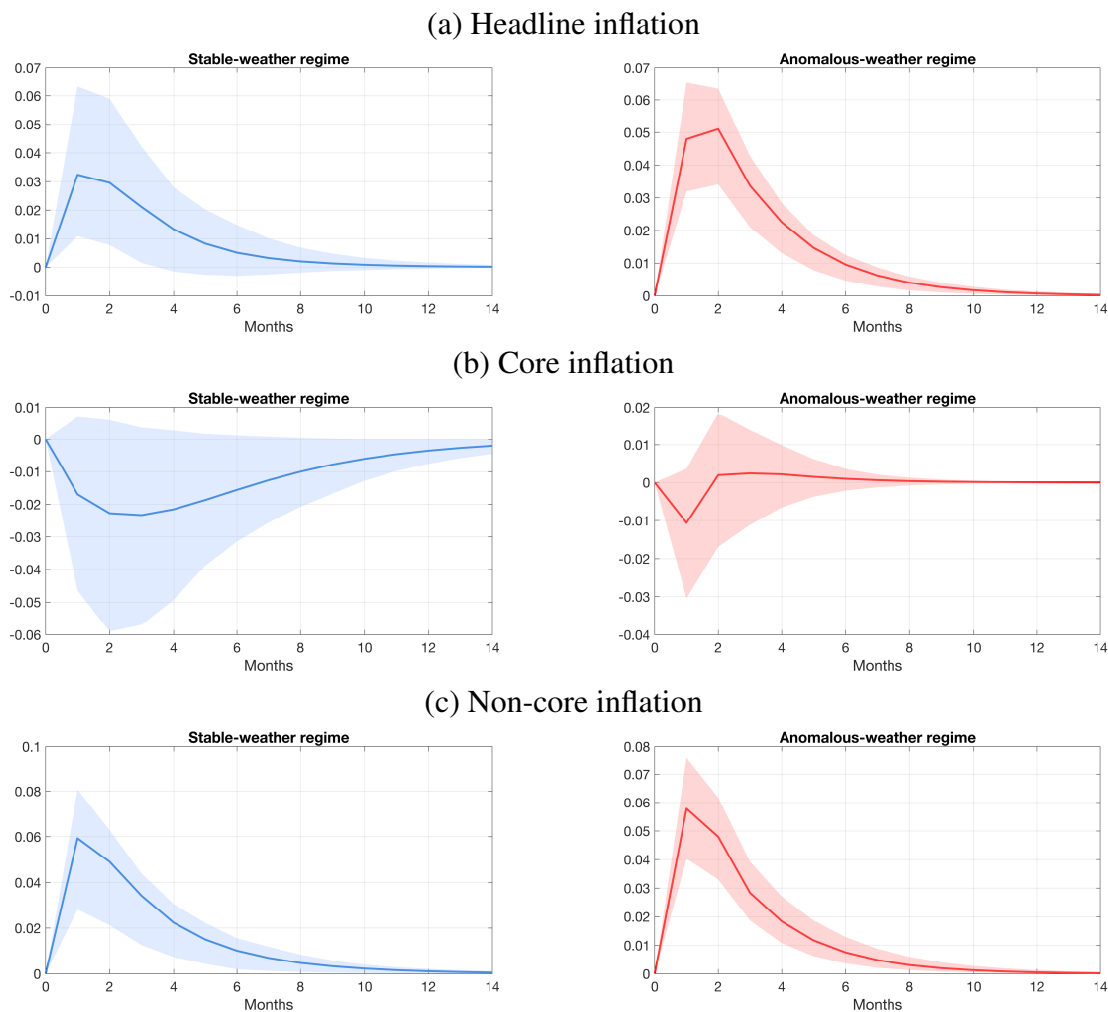
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime ($D_t = 0$, left graphs) and the anomalous weather regime ($D_t = 1$, right plots).

Figure 13: Impulse Response Functions of Inflation Measures to a One-Standard-Deviation Shock to the Weather Index Under Extreme Weather Conditions (Threshold VAR, 80th Percentile)



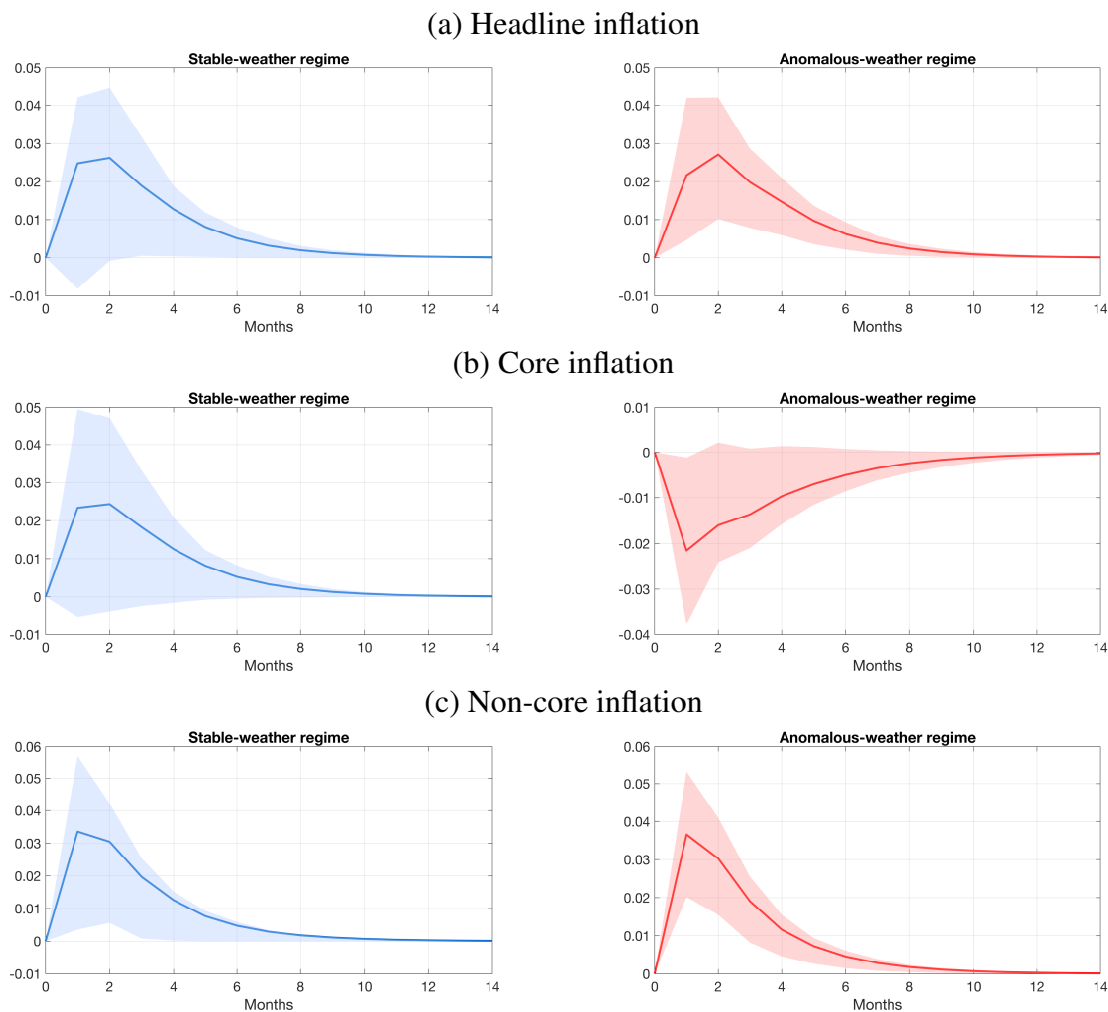
Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The left panels display responses under the low-weather-index regime (below the 80th percentile), while the right panels correspond to the high-weather-index regime (above the 80th percentile).

Figure 14: Impulse Response Functions of Inflation Variables to a One-Standard-Deviation Weather Shock in a SVAR Model Without Exogenous Controls



Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime ($D_t = 0$, left graphs) and the anomalous weather regime ($D_t = 1$, right plots).

Figure 15: Impulse Response Functions of Inflation Variables to a One-Standard-Deviation Weather Shock Using Pre-COVID-19 Data (Up to December 2019)



Notes. The shaded areas represent 90% confidence intervals, while the horizontal axis denotes the months following the weather index shock. The figure illustrates the dynamic effects under the stable weather regime ($D_t = 0$, left graphs) and the anomalous weather regime ($D_t = 1$, right plots).