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Effects of Weather Conditions on Prices in Korea†

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This paper examines the effects of unexpected changes in weather conditions on inflation in Korea. Using a structural vector autoregression (SVAR) model, we analyze how changes in temperature and precipitation influence price dynamics across different components of the consumer price index (CPI). Our empirical analysis reveals that unexpected changes in weather indices induce significant volatility in fresh food prices and exert direct impacts on consumer inflation, with precipitation changes contributing more substantially to short-term price increases than temperature variations. The effects are particularly pronounced during summer. However, core inflation, which excludes volatile food and energy components, remains largely unresponsive to weather indices. Through a regression analysis examining the interaction between headline and core inflation, we find that consumer prices tend to revert to core inflation levels, suggesting that weather-induced price fluctuations have limited medium-term impacts on the underlying inflation trend. These findings indicate that while weather changes may increase short-term price volatility through agricultural supply disruptions, monetary policy responses to such temporary fluctuations may be ineffective. Accordingly, alternative policy measures focusing on supply diversification and climate resilience should be prioritized.

Key Words: Climate Change, Inflation, Monetary
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I. Introduction

In recent years, the prices of fresh food, in particular fresh fruits, have experienced substantial increases. These abrupt fluctuations in the prices of agricultural products can exert significant pressure on household living costs. Such price volatility may generate spillover effects not only on consumption and inflation dynamics but also in the broader macroeconomic environment. Consequently, a growing discourse has emerged among economists and policymakers concerning the appropriate role of monetary policy in addressing this issue. Some posit that the recent surge in agricultural prices reflects more than a transitory shock, potentially altering the underlying trajectory of consumer prices and thereby justifying a monetary policy response. Others, however, argue that the volatility in fresh food prices is temporary in nature, rendering monetary intervention an ineffective and potentially inappropriate instrument for mitigating such short-term disturbances.

This raises the following question: What are the underlying causes of the recent sharp fluctuations in fresh food prices, including agricultural products? A primary factor contributing to the recent spikes in agricultural prices is declining crop yields, largely attributable to climate change and increasingly adverse weather conditions. In recent years, unexpected changes in weather conditions have disrupted agricultural production, leading to supply shortages. When supply fails to meet demand, upward pressure on prices is a natural outcome. These disruptions have become more frequent and widespread. For instance, unexpected heavy rainfall and a lack of sunshine in summer have led to poor harvests of fruits and vegetables, causing notable price increases. Over the past decade, precipitation in summer has become more volatile, and the probability of abnormal weather events has risen alongside the accelerating pace of global warming. As a result, such disruptions have been occurring with growing regularity, affecting different crop types in succession. Of course, climate-related price disruptions can be mitigated through adaptation effects. For instance, developing climate-resilient crop varieties or advancing agricultural technologies can help reduce the impact of adverse weather conditions. However, these adaptations typically require substantial time to take effect. As observed in recent cases, climate-related price shocks tend to occur with intensity and irregularity, exerting short-term effects on prices.

If climate change were merely a short-term or irregular phenomenon, there is likely no major cause for concern. However, the increasing severity and persistence of climate- related disruptions suggest otherwise. As global warming accelerates, the likelihood of extreme weather events increases. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (Masson-Delmotte *et al*., 2021) points out the likelihood of extreme weather events increasing as global warming intensifies. This escalation in climate variability complicates predictions of future weather patterns and managing climate-related risks. Sheshadri *et al*. (2021) highlights how mid-latitude error growth in atmospheric general circulation models plays a significant role in these challenges, particularly through the growth rate of atmospheric eddies.

As noted earlier, changes in climate conditions can significantly affect

agricultural yields, with consequent ramifications with regard to fresh food prices. In particular, fluctuations in temperatures and precipitation levels exert a direct influence on crop development. Extreme weather events—such as heatwaves, cold snaps, heavy rainfall, or prolonged droughts—can significantly reduce agricultural output, thereby driving pronounced price volatility in agricultural markets. For these reasons, it is essential to systematically analyze the impact of changing weather conditions, driven by climate change, on the prices of agricultural and fresh food products and to assess the corresponding implications pertaining to overall price indices.

Climate change is increasingly shaping economic outcomes, influencing not only the level and volatility of prices but also the broader macroeconomic landscape in Korea. The economic consequences of climate change can be broadly categorized into direct and indirect effects, both of which have significant implications regarding economic stability, policymaking, and long-term growth trajectories. Among the indirect effects, a key channel operates through the formation of expectations. Specifically, shifts in climatic conditions can alter the expectations of households and firms regarding future economic developments, thereby influencing consumption patterns, investment decisions, and overall economic activity.

Direct impacts of climate change can be classified further into physical and transition- related effects. Physical impacts refer to tangible disruptions caused by climate change, including extreme weather events and gradual environmental shifts. Extreme weather events—such as floods, earthquakes, and abnormal temperature fluctuations—typically have short- to medium-term consequences. In contrast, gradual changes, such as rising sea levels and increasing average temperatures, represent long-term transformations that can significantly affect the macroeconomy, primarily exerting their influence over extended periods.

Transition-related impacts are closely tied to efforts to adapt to climate change, particularly during the transition to a low-carbon economy. These impacts encompass the economic consequences of decarbonizing industrial structures to achieve carbon neutrality. As the Korean government seeks achieve a carbon-neutral society by 2050 (“2050 Carbon Neutrality”), all economic agents must adapt to this structural transformation, promising both opportunities and challenges across various sectors.

In general, climate change affects prices through both direct and indirect channels, operating via supply-side and demand-side mechanisms. For example, natural disasters such as floods and earthquakes can generate multifaceted economic impacts. These events not only disrupt production and reduce private consumption but also transmit their effects through broader economic linkages. Direct impacts refer to the immediate physical damage to production facilities and agricultural infrastructure, primarily affecting the supply side by hindering output and disrupting distribution networks. Additionally, such disasters can directly reduce household incomes, thereby weakening aggregate demand. Indirect effects emerge when natural disasters in one region cause cascading disruptions throughout supply chains, amplifying the initial supply-side shock beyond the directly affected area. On the demand side, indirect effects may arise as consumers adjust their consumption patterns in response to price increases—such as substituting away from specific food items—thereby influencing

demand for related goods. Among these various transmission mechanisms, the recent surge in fresh food prices in Korea attributed to climate change has been primarily driven by supply-side factors. Consequently, recent policy and academic discussions have increasingly emphasized the role of supply-side dynamics in understanding climate-induced price shocks.

This paper examines how unexpected changes in weather conditions from historical norms affect inflation in Korea. Prices of fresh fruits, such as apples, have recently become more volatile due to climate change. These climate-related disruptions occur more frequently each year and affect different crops. We empirically analyze whether such disruptions have a substantial impact on price levels. Based on the findings, we derive implications for monetary policy. Specifically, this paper conducts an empirical analysis of the impact of changes in weather conditions on inflation. As the primary analytical framework, a structural vector autoregression (SVAR) model is employed. Based on this model, the effects of climate-related shocks, particularly temperature and participation, on price levels are identified through impulse response functions. In addition, the study investigates the interaction between headline inflation—which includes the fresh food price index, known to be highly sensitive to climate fluctuations—and core inflation, which excludes such volatile components. This relationship is examined through a regression analysis to assess the extent of spillover effects between these two measures of inflation.

Our results fall into two main categories. First, the empirical analysis reveals that variations in weather indices significantly affect fresh food prices and directly influence consumer inflation. In particular, variations in the precipitation index contribute to short-term increases in consumer prices. However, while weather indices are linked to temporary spikes in fresh food prices, their effects on core inflation are minimal.

This suggests that unexpected weather fluctuations may lead to short-term inflationary pressures, but they do not substantially alter the underlying long-term trend of price levels. Moreover, the effects were more pronounced during the summer months, particularly when unexpected variations in precipitation occurred. However, core inflation remained largely unaffected by such weather-related changes.

Second, we found that changes in consumer prices caused by variations in weather indices have a negligible effect on core inflation. These results suggest a unidirectional adjustment mechanism: while consumer prices tend to revert to the level of core inflation, core inflation does not respond to changes in consumer prices. This implies that fluctuations in food and energy prices have limited medium-term effects on inflation overall. In other words, even when fresh food prices experience sharp short-term increases, consumer prices demonstrate a strong tendency to return to core inflation levels. Thus, the analysis indicates that temporary rises in fresh food prices do not have a lasting impact on the underlying inflation trend.

This paper proceeds as follows. Section 2 reviews related literature. Section 3 examines the impact of unexpected changes in weather conditions, such as temperature and precipitation, on price levels. Section 4 analyzes the interaction between headline inflation and core inflation. Section 5 concludes the paper.

II. Related Literature

A substantial body of empirical study has investigated the impact of the physical consequences of climate change on the broader macroeconomy, including price dynamics (cf., Dell *et al*., 2014; Batten, 2018). Building on this literature, this paper empirically examines how the physical impacts of climate change—particularly those influencing the demand side—affects price fluctuations.

Empirical studies of the relationship between climate change and inflation tend to focus on empirically identifying and quantifying the short- to medium-term macroeconomic effects of climate shocks. Cevik and Jalles (2024) empirically demonstrate that climate shocks asymmetrically impact inflation and growth, with advanced economies facing prolonged inflationary pressures from temperature extremes, while developing nations experience growth constraints due to droughts. Building on this, Kara and Thakoor (2023) propose a modified Taylor rule in a New Keynesian DSGE framework, indicating balanced responses to inflation and output volatility under recurrent climate shocks and emphasizing skewness in economic outcomes. Complementing these findings, Kim *et al*. (2025) employ smooth transition VAR to reveal time-varying macroeconomic impacts in the U.S., showing that severe weather has increasingly suppressed industrial production while elevating unemployment and inflation since the 1960s. Kotz *et al*. (2024) quantify climate-driven inflation dynamics globally, projecting 2035 food inflation increases of 0.9–3.2%p annually and highlighting seasonal shifts in price pressures at higher latitudes. Kabundi *et al*. (2022) further disentangle these dynamics, identifying droughts as persistently inflationary through food supply shocks, while floods exhibit disinflationary effects via demand contraction—a dichotomy particularly challenging for inflation-targeting regimes in low-income economies.

Studies with a stronger emphasis on policy design explore structural response strategies, such as optimal carbon taxation, integrated climate-monetary frameworks, and projections of the impact of climate change on long-term economic growth to inform policy designs. Nakov and Thomas (2023) stress that optimal carbon taxes eliminate monetary policy trade-offs, though suboptimal taxation scenarios marginally favor price stability over climate objectives during transitional periods. McKibbin *et al*. (2020) theoretically bridge this gap, advocating for integrated climate-monetary frameworks to manage supply shocks and inflation forecasting uncertainties. Kahn *et al*. (2021) provide cross-country evidence that persistent temperature deviations from historical norms reduce long-term GDP growth, projecting a 7.2% global per capita income loss by 2100 under unmitigated warming, which the Paris Agreement could mitigate to 1.1%. Andersson *et al*. (2020) synthesize evidence of climate change as a structural supply shock, noting EU-specific risks from energy transitions and stranded assets while underscoring renewable energy's deflationary potential.

By synthesizing these research strands, this paper conducts an empirical analysis of how weather variability affects price dynamics in Korea and derives policy implications based on the findings. There is a limited body of research examining the

effects of climate change on price levels and macroeconomic conditions in Korea. Despite the scarcity of related studies, Chung *et al*. (2025) provides a comprehensive empirical investigation into the various ways climate change affects the real economy in Korea. The present paper is most closely related to Chung *et al*. (2025), as both conduct an empirical analysis of the impact of climate change on inflation with a specific focus on Korea. While Chung *et al*. (2025) focuses on regional heterogeneity and temporal asymmetries in the economic impacts of climate change, this paper is distinguished is that it prioritizes the derivation of policy implications. In particular, we examine both seasonal and annual asymmetries to identify the periods during which climate shocks have the greatest influence on price levels. Building on this analysis, we derive implications for monetary policy.

Recent studies exploring the macroeconomic implications of climate change, particularly on inflation or the role of central banks, tend to propose overarching monetary policy frameworks based on empirical analyses. For instance, Nakov and Thomas (2023) argue against the use of conventional monetary policy tools as instruments with which to address climate change and instead emphasize the importance of maintaining strict inflation targeting, even when carbon taxes are suboptimal. Similarly, McKibbin *et al*. (2020) stress the need to develop climate-adjusted inflation-targeting frameworks that explicitly account for climate-induced supply shocks. Kotz *et al*. (2024) also highlight the importance of incorporating climate variables into inflation forecasting models, thereby calling for a more climate-aware monetary policy framework. These studies both emphasize recommending forward-looking adjustments to monetary policy frameworks in anticipation of increasing climate risks. In contrast, this paper takes a more targeted approach, focusing not on normative policy recommendations but rather on assessing the continued effectiveness of the current monetary policy framework in the face of climate-induced risk. Specifically, rather than offering broad recommendations for overall monetary policy, this paper focuses on evaluating whether central banks need to respond to abrupt food price fluctuations driven by localized weather anomalies. Across the globe, unexpected shifts in weather conditions, such as extreme temperatures or abnormal precipitation events, have led to reduced agricultural yields and sharp increases in the prices of specific crops, thereby putting upward pressure on aggregate price indices. This paper adds to previous studies by providing policy recommendations that address a concrete phenomenon resulting from climate change, rather than offering general strategic directions.

III. Impact of Weather Condition Changes on Price Levels

To analyze the actual effects of unexpected changes in temperature and precipitation on inflation, an empirical analysis was conducted using a structural vector autoregression (SVAR) model. The analysis covers the period from January of 2003 to December of 2023 and incorporates important variables, in this case weather conditions, import prices, production, employment, inflation, and interest rates, aiming to capture the overall dynamics of the macroeconomy. The empirical strategy begins with an analysis of the overall consumer price index (CPI) as a baseline.

Subsequently, inflation is disaggregated into core CPI (excluding food and energy) and the fresh food price index[1] (hereafter, food CPI) to assess the differentiated effects of weather indices across distinct price components. The SVAR model in this paper is identified based on a recursive identification strategy. This approach requires the ordering of endogenous variables from the most exogenous to the most endogenous. We place weather indices first in the ordering, as weather conditions are largely exogenous to the economic system—that is, they are minimally influenced by other endogenous economic variables—while they can exert significant effects on the broader economy. Following this, import prices come next, reflecting the characteristics of Korea as a small open economy, where external price movements precede domestic economic adjustments. The remaining variables—production, employment, inflation, and interest rates—are ordered based on conventional practices in the empirical macroeconomic literature.[2] By placing the interest rate last in the ordering, the model is structured such that interest rate shocks respond to production, employment, and prices with a lag. In other words, the interest rate is treated as a lagged variable, exerting no contemporaneous effects.

The model specification can vary depending on the assumed exogeneity of weather conditions. For instance, Ciccarelli *et al*. (2024) assumes that weather conditions are fully exogenous. Based on this assumption, Ciccarelli *et al*. (2024) employs a VARX model to analyze the impact of weather on macroeconomic variables. In contrast, Kim *et al*. (2025) assumes that economic shocks do not have contemporaneous effects on weather conditions and accordingly adopts a VAR model. This paper takes an approach similar to that in Kim *et al*. (2025), rejecting the assumption of full exogeneity of weather conditions. The rationale is that economic activity can influence the climate with a time lag of several weeks or months. For example, Yang *et al*. (2022) and Braun and Schlenker (2023) demonstrate that irrigation in China and Unites States, respectively, can affect local temperature distributions with a delay. Specifically, Yang *et al*. (2022) and Braun and Schlenker (2023) empirically show that springtime irrigation reduces the likelihood of extreme weather events in summer. Liu *et al*. (2024) finds that black carbon emissions in South Asia are associated with a significant reduction in summer precipitation over Tibet, with a lag of three to four weeks. Building on these findings, we assume that weather conditions are not fully exogenous. Rather, they may be influenced by economic activity with a time lag of several months. Accordingly, we adopt a VAR framework that allows for this possibility.

To conduct the analysis, it is necessary to define a weather index measure that quantifies unexpected changes in meteorological conditions. Following earlier works

[1]The fresh food price index is composed of 55 specific items, including fresh fish and seafood, fresh vegetables, and fresh fruits. The prices of all of these items are highly volatile and may influence consumers' inflation expectations. As of 2024, the fresh food price index accounts for 3.8% of CPI, while the entire agricultural, livestock, and fisheries sector represents 7.6%. This indicates that the fresh food price index constitutes approximately half of the total price of the agricultural, livestock, and fisheries sector.

[2]Christiano *et al*. (1999) and Christiano *et al*. (2005) propose a method for identifying monetary policy shocks using a recursive VAR approach. Following these works, many subsequent studies adopted this recursive identification strategy as well (Stock and Watson, 2001; Faust and Rogers, 2003; Dedola and Lippi, 2005 among many).

(Kahn *et al*., 2021; Kabundi *et al*., 2022), weather indices in this paper are defined as in (1). To be specific, a weather index (WI) refers to the standardized deviation of the monthly average temperature and precipitation (X) from their respective historical trends ($\overline{X}$) —calculated as the 30-year average for the same calendar month.[3]

$$WI_{i,t} = \frac{x_{i,t} - \bar{x}_{i,-30:t-1}}{\sigma_{i,-30:t-1}} \quad \text{for } i = \text{temperature or precipitation} \qquad (1)$$

For instance, when the monthly average temperature deviates upward or downward from its historical monthly mean over the past 30 years, it is regarded as a temperature index. The magnitude of the index is measured using the standard deviation of the corresponding month over the 30-year historical period.[4] Similarly, deviations in monthly average precipitation from the historical trend are classified as a precipitation index.[5]

Kahn *et al*. (2021) and Kabundi *et al*. (2022) define the standardized deviations of weather variables as "weather shocks" and treat them as exogenous. Kahn *et al*. (2021) and Kabundi *et al*. (2022) estimate the corresponding impulse responses using Jordà's (2005) local projection method. However, as noted earlier, this paper does not treat weather variables as exogenous shocks despite the fact that they are standardized. Instead, we adopt a VAR framework that allows for the possibility that economic activity can influence weather conditions with a time lag.

Figure 1 illustrates the monthly average temperature, precipitation, and weather indices as defined in (1). As shown in the figure, both the monthly average temperature and precipitation have exhibited an increasing trend in recent years. When weather indices are defined as standardized deviations from the past 30 years, their scale becomes smaller and exhibits less variation compared to the original temperature and precipitation data.

This approach differs from the method based on the Actuaries Climate Index (ACI), developed by the American and Canadian actuarial societies and used in Kim *et al*. (2025) and Chung *et al*. (2025). Specifically, Kim *et al*. (2025) and Chung *et al*. (2025) construct the ACI using five components: extreme high temperatures, extreme low temperatures, heavy rainfall, drought, and the sea level. Each component is

(a) Temperature and Weather Index

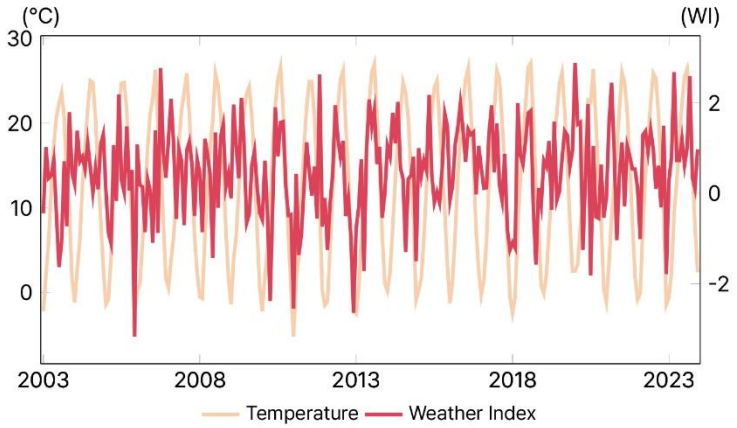
[3]The empirical analysis in this paper covers the period from January of 2003 to December of 2023. Because weather indices are defined as standardized deviations from the past 30 years, we use weather-related data from January of 1973 onward to construct the weather index variables.

[4]For example, the weather index (WI) for temperature in January of 2003 is defined as follows:

$$WI_{\text{Jan2003}} = \frac{\text{Temperature}_{\text{Jan2003}} - \text{Mean}_{\text{Jan(1993-2002)}}}{\text{Standard Deviation}_{\text{Jan(1993 2002)}}}$$

That is, it is calculated as the deviation of the January 2003 temperature from the average temperature in January over the period 1973–2002, standardized by the corresponding standard deviation.

[5]As a robustness check, we redefine the weather index using deviations from the past 10-year and 20- year historical averages, instead of the 30-year benchmark used in the baseline analysis. We then re-estimate the SVAR model and conduct an impulse response analysis. The empirical results remain robust across these alternative definitions of the weather index. This suggests that our findings are not sensitive to the specific historical window used to define weather shocks. These results are presented in Figure A1 and Figure A2 in Section A of the Appendix.



(b) Precipitation and Weather Index

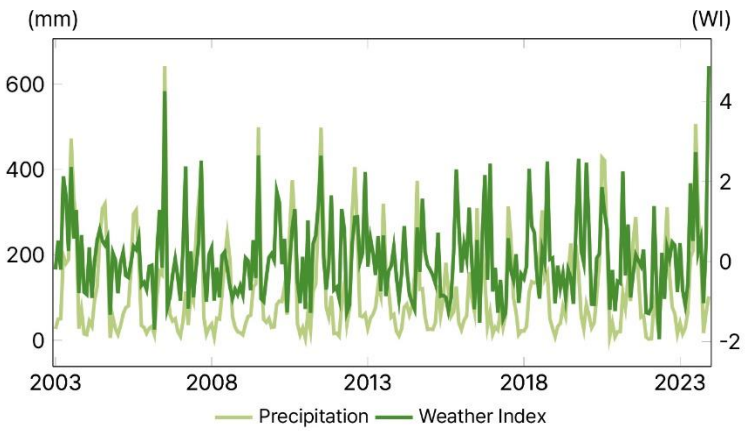


FIGURE 1. TEMPERATURE, PRECIPITATION, AND WEATHER INDICES (2003-2023)

Notes: Temperature (precipitation) refers to the average daily temperature (precipitation) within a given month. The weather index is defined as the deviation of the monthly average temperature (precipitation) from the 30-year historical average for the corresponding month, standardized by the 30-year historical standard deviation for that month.

Source: Korea Meteorological Administration (KMA).

standardized relative to a reference period, and the index is calculated as the average of these standardized components. This method has the advantage of capturing paper overall climate-related risks stemming from extreme weather events. However, this focuses on isolating the effects of temperature and precipitation. Therefore, instead of combining the components, we standardize and analyze them separately.[6]

[6]As a robustness check, we construct a composite weather index similar in form to the Actuaries Climate Index (ACI) and conduct an impulse response analysis. The composite index (WIcomposite) is defined as the simple average of the temperature and precipitation indices:

$$WI_{\text{composite}} = mean\{WI_{temperature},\ WI_{precipitation}\}$$

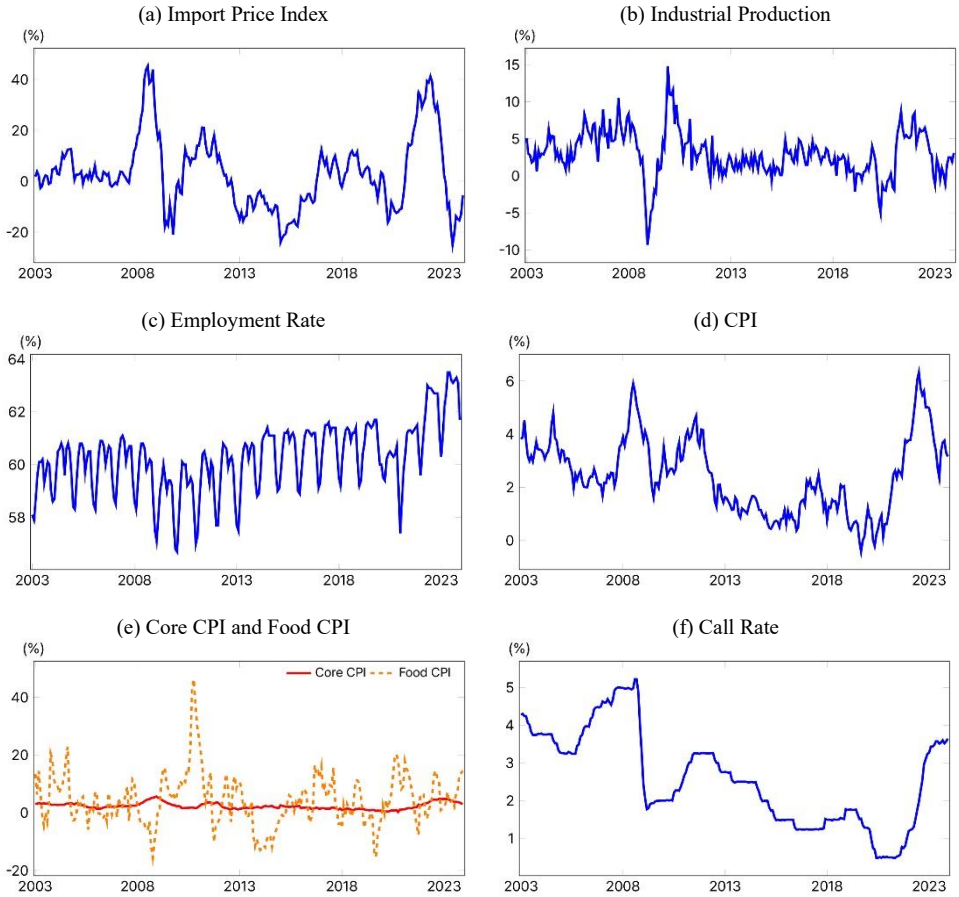


FIGURE 2. MONTHLY TIME SERIES FOR THE EMPIRICAL ANALYSIS (2003-2023)

Notes: Each panel in the figure presents the monthly time series of the macroeconomic variables used in the empirical analysis. For industrial production and price-related variables—including the import price index, CPI, core CPI, and food CPI—year-on-year growth rates are applied.

Source: Korean Statistical Information Service (KOSIS); Bank of Korea.

Including the weather index defined above, the endogenous variables in the SVAR model consist of weather indices, import prices, production, employment, prices, and interest rates. Specifically, two separate SVAR models are estimated: one using temperature as the weather variable and the other using precipitation. This allows for a distinct assessment of the effects of changes in each type of weather index on macroeconomic variables. The import price index is used to represent import prices,

This formulation closely follows the approach that uses the ACI (cf. Kim *et al*., 2025). Rather than including temperature and precipitation indices separately, we incorporate this composite index into the SVAR model and estimate the impulse responses of price variables. The results, presented in Figure B1 in Section B of the Appendix, are broadly consistent with those of the baseline analysis. Core CPI exhibits only minimal responses and does not react significantly to the weather index. In contrast, both CPI and food CPI respond to the weather index, with a notably larger effect on food CPI observed.

while the all-industry production index is used for production. The employment rate captures employment conditions, the call rate represents interest rates, and the consumer price index (CPI) is used to measure overall prices. To ensure the stationarity of the endogenous variables, year-on-year growth rates are applied to production-related and price-related variables. In contrast, employment and interest rate variables are included in levels, with appropriate controls for time trends.

Figure 2 illustrates presents the monthly macroeconomic variables used in the empirical analysis, covering the period from January of 2003 to December of 2023. In particular, Panel (e) displays the core CPI and food CPI components of the overall CPI shown in Panel (d). A comparison between core CPI and food CPI reveals that core CPI, which excludes volatile items such as food and energy, exhibits relatively stable trend. In contrast, food CPI, which includes agricultural and livestock products, shows substantial month-to-month fluctuations. For this reason, we also examine the effects of changes in weather indices not only in relation to the overall CPI but also for the corresponding core and food components. To be specific, we separate prices into fresh food prices and core inflation to examine the differential effects of weather indices on each price indicator. Given that weather index variations can influence prices both through delayed demand-side effects and immediate supply-side disruptions in agricultural commodities, it is assumed that core prices are more endogenous than fresh food prices. This assumption reflects the notion that weather-induced fluctuations in fresh food prices can shape expectations regarding broader inflation, thereby affecting core prices. However, under short-term constraints, core prices are assumed not to influence fresh food prices.

Based on the SVAR model defined earlier, we estimate the model and analyze the impulse response functions to assess the effects of changes in temperature and precipitation indices on price dynamics.[7] As mentioned earlier, the baseline model uses CPI as the primary measure of inflation. In additional analyses, the CPI is disaggregated into core CPI and food CPI to investigate the differentiated impacts of weather indices further.

Each panel in Figure 3 illustrates the effects of a one-standard-deviation weather index[8]—either in temperature or precipitation—on price indices, including the CPI, food CPI, and core CPI. In general, the price indices respond by rising and typically reach their peak approximately two months after the shock occurs. However, from the third month onward, the responses become negligible, indicating that variations of the weather indices primarily exert short-term effects on consumer prices. Such short-term and moderate responses of prices to weather shocks are consistent with findings from previous studies (Kabundi *et al*., 2022; Cevik and Jalles, 2024; Kim *et al*., 2025). It is important to note that the impulse response functions are estimated

[7]The VAR model uses a lag length of 3. While lag selection in VAR models can be based on various criteria, this paper selects a lag length of 3, as this value minimizes the forecast error over the period of 2021 to 2023. Given that empirical studies using monthly data commonly adopt lag lengths in multiples of three, the choice of lag 3 also aligns with conventional practices. As a robustness check, alternative lag selection criteria, in this case the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), suggest a lag of 4. However, the impulse response functions remain qualitatively similar and robust under this alternative specification.

[8]Over the sample period, the standard deviation of the monthly average temperature was 9.2℃, and that of the monthly average precipitation was 106.8mm.

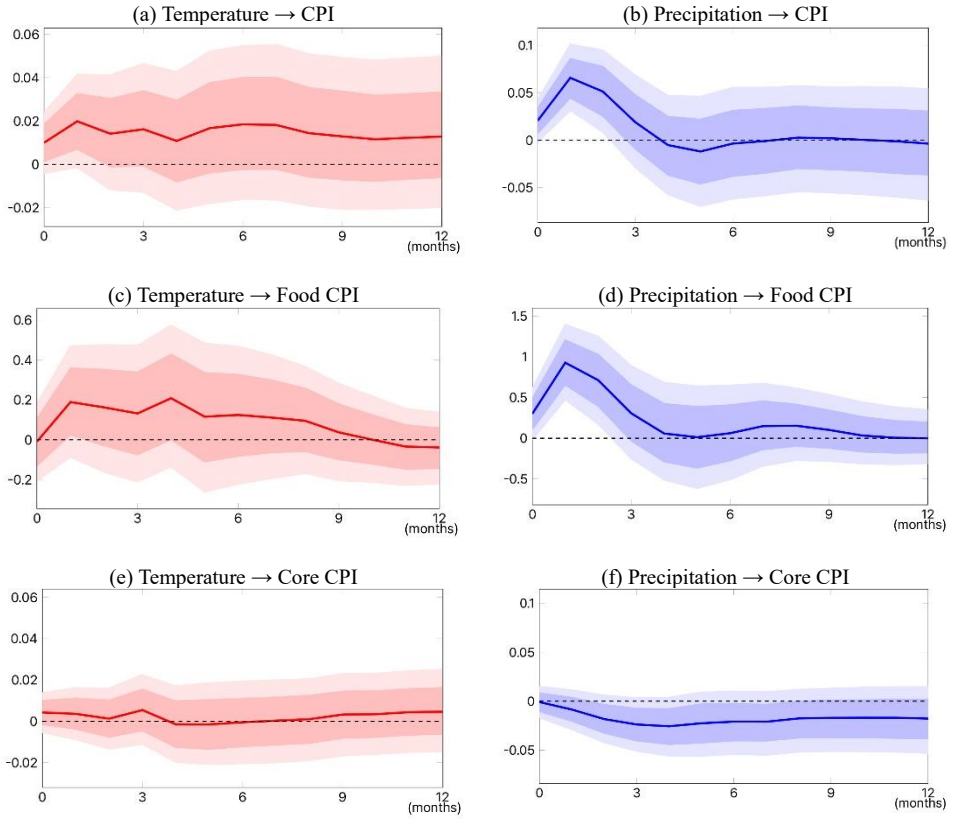


FIGURE 3. IMPULSE RESPONSES OF TEMPERATURE AND PRECIPITATION SHOCKS ON PRICES

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to weather shocks.

under the assumption that the weather shock occurs only once, within a single month. Therefore, if weather shocks were to persist for two to three consecutive months, their effects could accumulate, potentially leading to a more pronounced impact on prices.

We examine how prices respond to changes in weather indices in more detail. The panels on the left in Figure 3 reveal that all price indices—CPI, food CPI, and core CPI—respond positively to temperature shocks. Nevertheless, the wide confidence intervals indicate that these responses are not statistically significant. When examining the magnitude of the responses, it is evident that the core CPI responds minimally to temperature shocks, while the food CPI exhibits greater sensitivity. Consequently, the overall CPI shows a smaller response, primarily reflecting the impact of the food CPI. The panels on the right in Figure 3 show the price responses to a precipitation shock. Overall, the interpretation is similar to that of the response to a temperature shock. However, in this case, both the overall CPI and the food CPI exhibit statistically significant responses to the precipitation shock. In other words, compared to temperature shocks, precipitation shocks have a more pronounced and statistically significant short-term impact on the food CPI, which in turn drives a

significant response in the overall CPI. As in the previous analysis, the core CPI remains largely unresponsive to such a shock, whereas the food CPI shows a relatively strong reaction. The finding that the core CPI exhibits little to no response to both temperature and precipitation shocks—and that these effects are statistically insignificant—is consistent with previous studies. In particular, in advanced economies where central banks conduct monetary policy independently under an inflation-targeting framework and where fiscal capacity is sufficient, core inflation tends to remain largely unaffected by weather indices (Kabundi *et al*., 2022; Cevik and Jalles, 2024).

The impact of weather shocks on prices may be asymmetric depending on the sign of the shock (i.e., positive or negative). For instance, a positive temperature shock indicates temperatures higher than the historical average, while a negative shock reflects lower-than-average temperatures. To examine the potential asymmetric responses of prices to changes in weather indices, we construct positive and negative weather indices. The positive index is defined as the weather index when its value is positive and zero otherwise. The negative index is defined similarly. SVAR models are estimated separately using each index, and the corresponding impulse response functions are derived accordingly.

Figure 4 illustrates the asymmetric impulse responses of weather shocks on prices. In each panel, the solid red line represents the impulse response to a positive weather shock, while the solid blue line represents the response to a negative weather shock. For temperature shocks, shown in the panels on the left of the figure, neither positive nor negative shocks have a statistically significant effect on the overall CPI or core CPI. However, a positive temperature shock has a significant impact on the food CPI, suggesting that temperatures above historical averages tend to raise food prices. The impulse responses to precipitation shocks, shown in the panels on the right, reveal more notable results. Both positive and negative precipitation shocks have statistically significant effects on the CPI, with the impact of positive shocks being slightly larger. These CPI responses appear to be primarily driven by the food CPI, as both positive and negative precipitation shocks lead to increases in the food CPI. This finding implies that deviations in precipitation—whether excessive or insufficient—relative to historical averages can lead to higher food prices, likely due to the increased risk of flooding or drought. These results are consistent with intuitive expectations.

To investigate the mechanisms underlying the asymmetric impulse responses further, we consider seasonal effects. The impact of changes in weather indices on prices can vary depending on (1) the season in which the change occurs and (2) whether the change of weather indices represents a deviation above or below the historical average (i.e., a positive or negative index). For example, the effect of higher-than-usual summer temperatures on prices may differ from that of warmer-than-usual winters, even though both constitute positive indices. To account for this asymmetry and seasonal heterogeneity, we classify weather indices into eight categories based on both the season and the direction of deviation from the historical average. Specifically, we construct interaction terms by multiplying seasonal dummy variables[9]

[9]Seasons are defined as follows: spring includes March to May, summer includes June to August, autumn

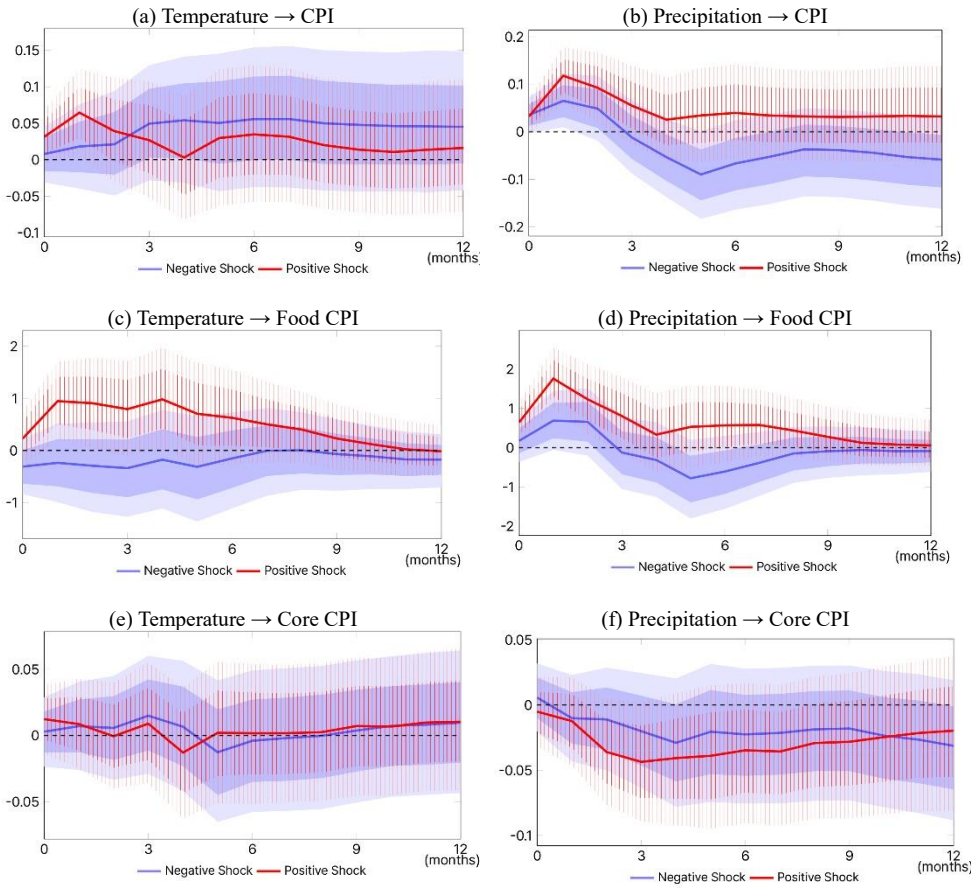


FIGURE 4. ASYMMETRIC IMPULSE RESPONSE OF TEMPERATURE AND PRECIPITATION SHOCK ON PRICES

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light blue shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to negative weather shocks. Likewise, the dark and light red vertical lines indicate the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to positive weather shocks.

by either the positive or negative weather indices. For example, to analyze the effects of variations of positive temperature indices in summer, we construct a new index by multiplying the summer dummy variable with the previously defined positive temperature index. Using these terms as new indices, we estimate their respective effects on the CPI, core CPI, and food CPI.

Our empirical results show that the impact of changes in weather indices on prices is more pronounced during the summer.[10] The finding that summer weather exerts a stronger influence on price dynamics compared to other seasons is consistent with previous studies (Faccia *et al*., 2021; Ciccarelli *et al*., 2024). Figure 5 presents the

includes September to November, and winter includes December to February.

[10]For the spring, autumn, and winter seasons, the CPI, core CPI, and food CPI generally did not exhibit significant responses to either temperature or precipitation shocks. Detailed results are provided in Figure C1-Figure A3 in Section C of the Appendix.

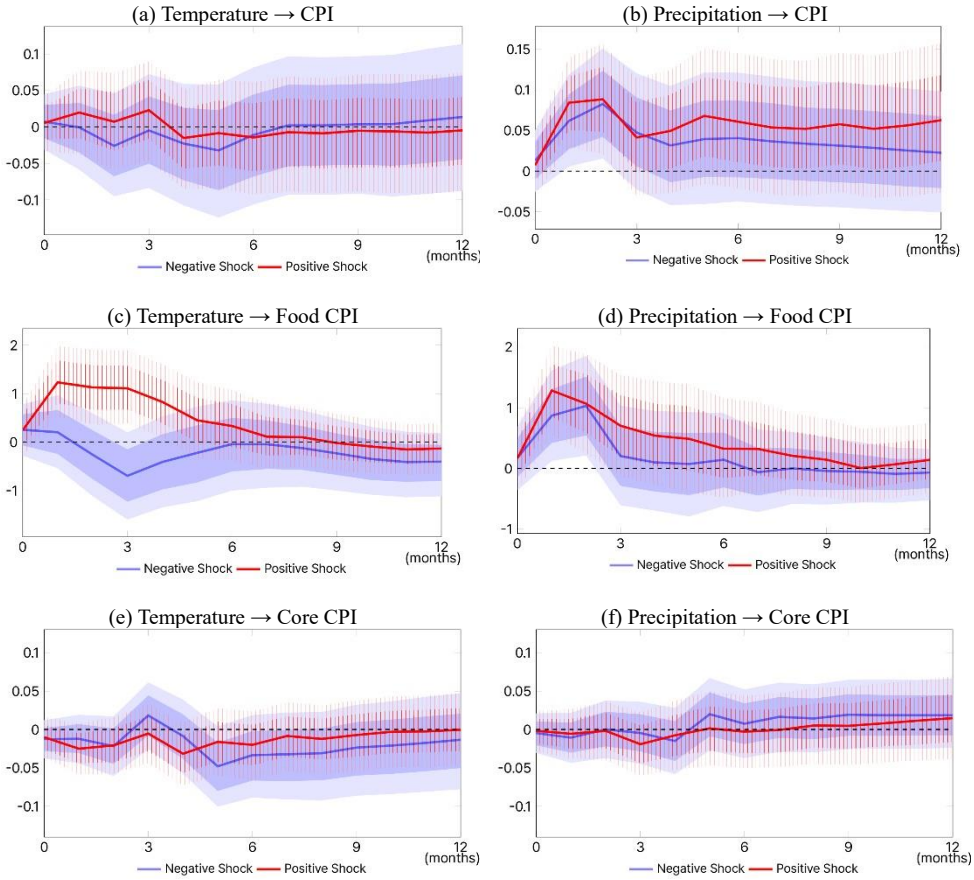


FIGURE 5. IMPULSE RESPONSES OF TEMPERATURE AND PRECIPITATION SHOCK ON PRICES IN SUMMER

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light blue shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to negative weather shocks. Likewise, the dark and light red vertical lines indicate the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to positive weather shocks.

effects of summer temperature and precipitation shocks on prices. Regarding summer temperatures, abnormal heat events led to a statistically significant increase in fresh food prices, whereas the overall CPI did not exhibit a statistically significant response. When unusually low temperatures occurred during the summer, price indices showed little to no reaction. Regarding summer precipitation, both excessive and insufficient rainfall—relative to historical trends—had significant effects on fresh food prices, thereby contributing to the upward pressure on the CPI. However, even under these conditions, core inflation remained largely unresponsive to weather indices. These findings suggest that if the intensity and frequency of variations in weather indices increase in the future, the heterogeneous effects of such variations on prices could lead to greater changes in inflation. In particular, the stronger impact of weather during the summer implies that climate anomalies, such as extreme heat

and heavy rainfall, occurring more frequently and intensely due to global warming, may further amplify price volatility.

IV. Interaction between Headline and Core Inflation

As demonstrated in the preceding analysis, the impact of weather-induced spikes in fresh food prices on the overall CPI appears to be limited and short-lived. However, it remains important to examine in greater depth whether such price surges influence the underlying trend of consumer inflation. The core CPI, which excludes volatile items such as food and energy, serves as a key indicator for analyzing the long-term trajectory of inflation. Therefore, to assess whether sharp increases in fresh food prices due to weather indices contribute to sustained inflationary pressure, we conduct a regression analysis examining the interaction between the headline CPI and core CPI.[11]

To conduct this analysis, we consider two regression models. The first model investigates whether inflation tends to revert to the level of core inflation. Following Clark (2001), the explanatory variable is the difference in growth rates between the CPI and core CPI $(\pi_t - \pi^c)$, driven by fluctuations in food and energy prices, while the dependent variable is the change in CPI growth h months later $(\pi_{t+h} - \pi_t)$. This relationship is formalized in (2).

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h(\pi_t - \pi^c) + \varepsilon_{t+h} \tag{2}$$

In this model, the CPI–core CPI growth differential at time t serves as the regressor, and the change in the CPI growth rate between time t and $t+h$ is the outcome variable.

The key parameter of interest is the regression coefficient of the explanatory variable, βh. A negative coefficient of implies that even when headline inflation diverges from core inflation due to food and energy price shocks, the CPI subsequently reverts to the level of core inflation. A coefficient of –1 would suggest full mean reversion, indicating that the effect of food and energy price shocks dissipates entirely over time.

The second regression analysis examines whether core inflation tends to revert to the level of headline inflation. In contrast to the first analysis, this model reverses the roles of the CPI and core CPI by using the growth differential as the explanatory variable and the subsequent change in core inflation as the dependent variable (Cecchetti and Moessner, 2008). As in the previous model, a negative regression coefficient would indicate that core inflation reverts toward the level of headline inflation. This model is described in (3), as follows.

[11]The following regression analysis demonstrates that temporary fluctuations in the food CPI do not have a significant impact on the core CPI. To support this finding further, we also conduct an impulse response analysis of a food CPI shock on the core CPI using the SVAR framework. These results are presented in Figure D1 in Section D of the Appendix. The impulse responses of the core CPI to food CPI shocks remain statistically insignificant, even over a longer horizon of up to 24 months.

$$\pi^{c}_{t+h} - \pi^{c}_{t} = \gamma_h + \delta_h(\pi^{c}_{t} - \pi_t) + \varepsilon_{t+h} \tag{3}$$

If fluctuations in fresh food prices—or food and energy prices more broadly—do not affect the underlying inflation trend, we would expect to observe reversion in the first regression (CPI converging to core CPI), but not in the second (core CPI reverting to CPI). Through this dual analysis, we assess the medium-term impact of changes in food and energy prices on overall consumer price inflation.

We would not expect core inflation to revert to headline inflation if temporary fluctuations of food and energy prices do not influence the underlying inflation trend. The empirical results support this hypothesis: headline inflation tends to revert to core inflation, while core inflation does not revert to headline inflation. This suggests that the medium-term impact of food and energy price fluctuations on overall consumer prices is limited.

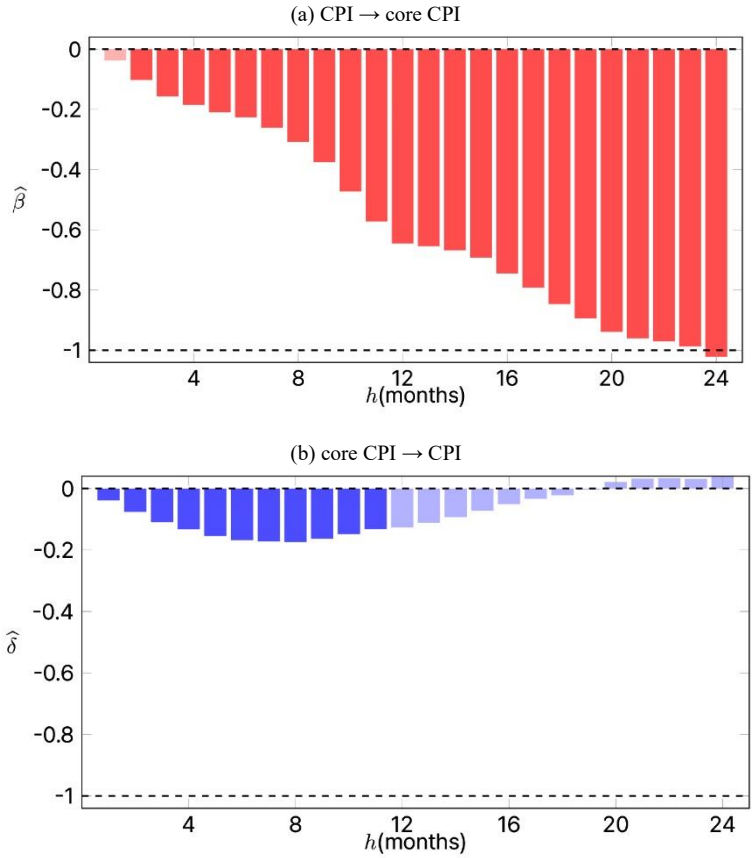


FIGURE 6. CONVERGENCE BETWEEN HEADLINE AND CORE INFLATION

Notes: The null hypothesis is that the regression coefficient (β or δ) equals zero. Dark bars indicate statistical significance at the 5% level, while light bars indicate coefficients not significantly different from zero at the 5% level.

In particular, even when fresh food prices experience sharp temporary increases, headline inflation shows a strong tendency to return to the level of core inflation. Figure 6 presents the estimated regression coefficients from the two models described earlier. As shown in the upper panel of Figure 6, headline inflation converges to core inflation over time. Specifically, approximately two-thirds of the deviation between CPI and core CPI—caused by fluctuations in fresh food and energy prices—disappears within one year, and the gap fully closes within two years.

In contrast, the lower panel in Figure 6 shows that core inflation exhibits little tendency to revert to headline inflation. The regression coefficient initially appears to be slightly negative, but overall, the estimated coefficients are not statistically significant. These findings indicate that temporary spikes in fresh food prices do not significantly affect the underlying trend of inflation.

Taken together, these results suggest that increases in fresh food prices due to changing weather conditions have only short-term effects on consumer prices. Therefore, from a medium-term perspective, monetary policy aimed at price stability may be limited with regard to any need to respond to consumer price increases caused by poor harvests.

V. Conclusion

This paper presents an empirical analysis centered on Korea, comprehensively examining the effects of changes in temperature and precipitation indices on prices. It also investigates the transmission effects between the inflation and core inflation. The results show that changes of weather indices significantly affect consumer prices in the short term, mainly through fresh food prices, while the impact on core inflation is minimal.

It is particularly noteworthy that both upward and downward deviations in summer precipitation from historical trends have a significantly stronger impact on prices. Given global warming and the expected rise in the frequency and intensity of extreme summer weather events, the impact of changes in weather conditions on prices is likely to grow.

Additionally, the study examines the medium-term effects of differences between consumer prices and core inflation caused by fresh food price volatility. The findings indicate that consumer prices tend to revert to core inflation, while core inflation rarely reverts to consumer prices. Abrupt changes in fresh food prices can lead to a temporary divergence between headline CPI and core inflation, occasionally fueling inflation expectations and causing short-lived increases in core inflation. Nevertheless, such effects are typically limited in terms of their magnitude and duration, with consumer prices eventually reverting to their underlying trend.

The results suggest that the impact of changes in weather indices on fresh food prices primarily leads to short-term fluctuations in consumer prices, with minimal effects on core inflation. Even during the summer season, when changes in weather indices have the strongest influence, increased volatility in fresh food prices does not pose a significant risk to price stability from a medium-term perspective. Therefore, it is not advisable for monetary policy to react sensitively to such temporary fluctuations

in fresh food prices. Instead, policy measures aimed at mitigating the impact of fresh food price increases on consumer prices should consider diversifying supply sources, such as expanding agricultural imports, to address supply shortages. Moreover, reducing the instability of agricultural production caused by climate change requires long-term strategies focused on sustainable agricultural policies and on enhancing climate resilience. This will be a crucial task as part of the effort to minimize economic shocks in the face of inevitable climate change in the future.

APPENDIX

A. *Alternative Specifications of the Weather Index*

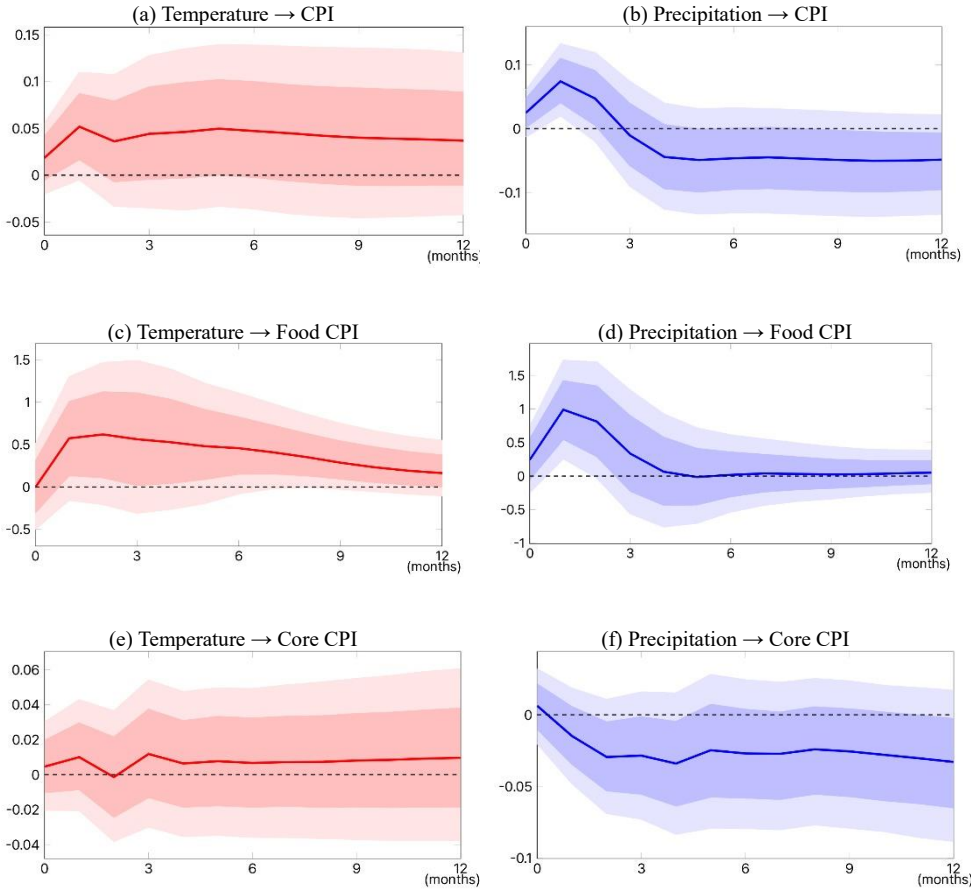


FIGURE A1. STANDARDIZATION RELATIVE TO THE 10-YEAR HISTORICAL AVERAGE

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to weather shocks. Weather indices are standardized based on deviations from the 10-year historical average.

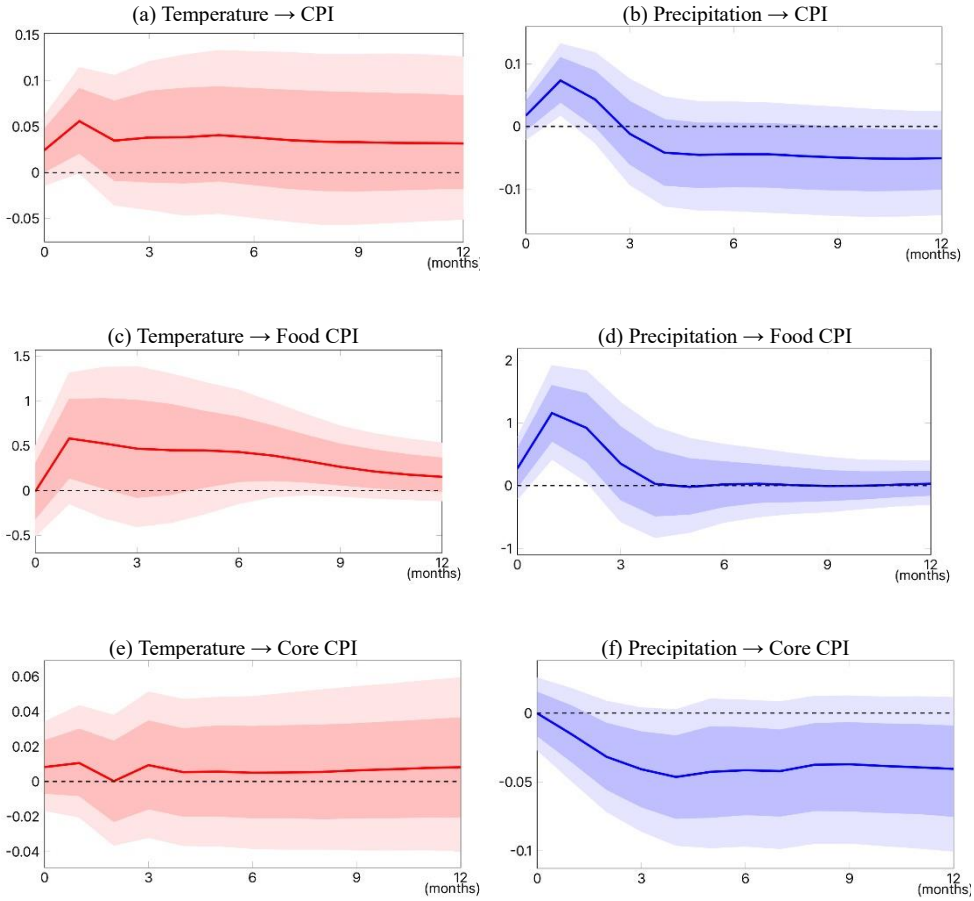


FIGURE A2. STANDARDIZATION RELATIVE TO THE 20-YEAR HISTORICAL AVERAGE

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to weather shocks. Weather indices are standardized based on deviations from the 20-year historical average.

B. *Impulse Responses to the Composite Weather Index*

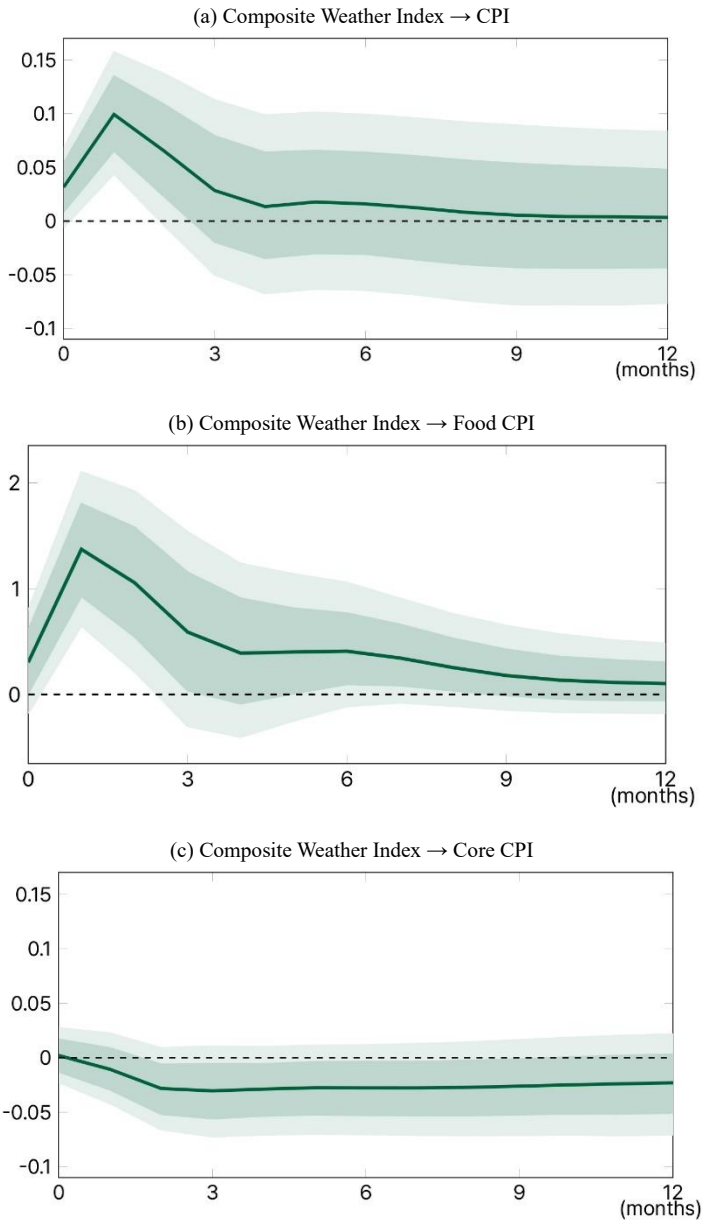


FIGURE B1. IMPULSE RESPONSES TO THE COMPOSITE WEATHER INDEX

Notes: Each panel in the figure presents the impulse responses of price levels to a composite weather shock. The dark and light shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to a composite weather shock.

C. *Seasonal Heterogeneity of Price Responses*

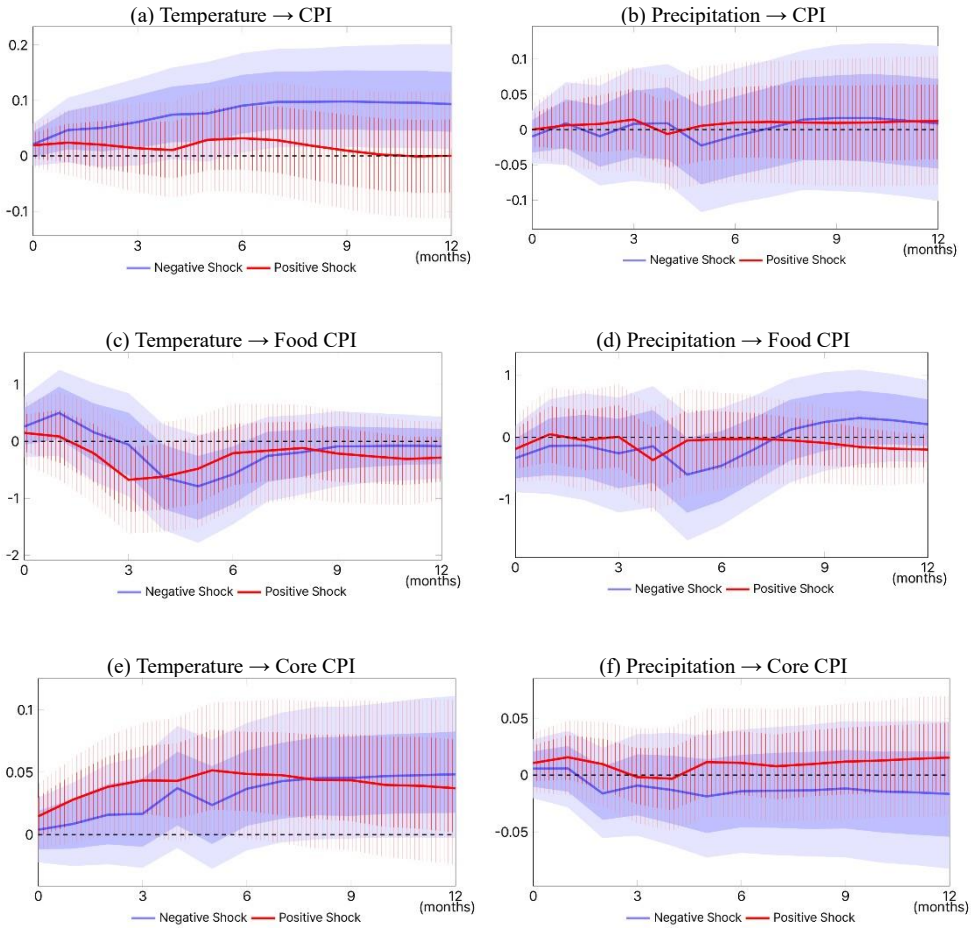


FIGURE C1. IMPULSE RESPONSES OF TEMPERATURE AND PRECIPITATION SHOCKS ON PRICES IN SPRING

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light blue shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to negative weather shocks. Likewise, the dark and light red vertical lines indicate the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to positive weather shocks.

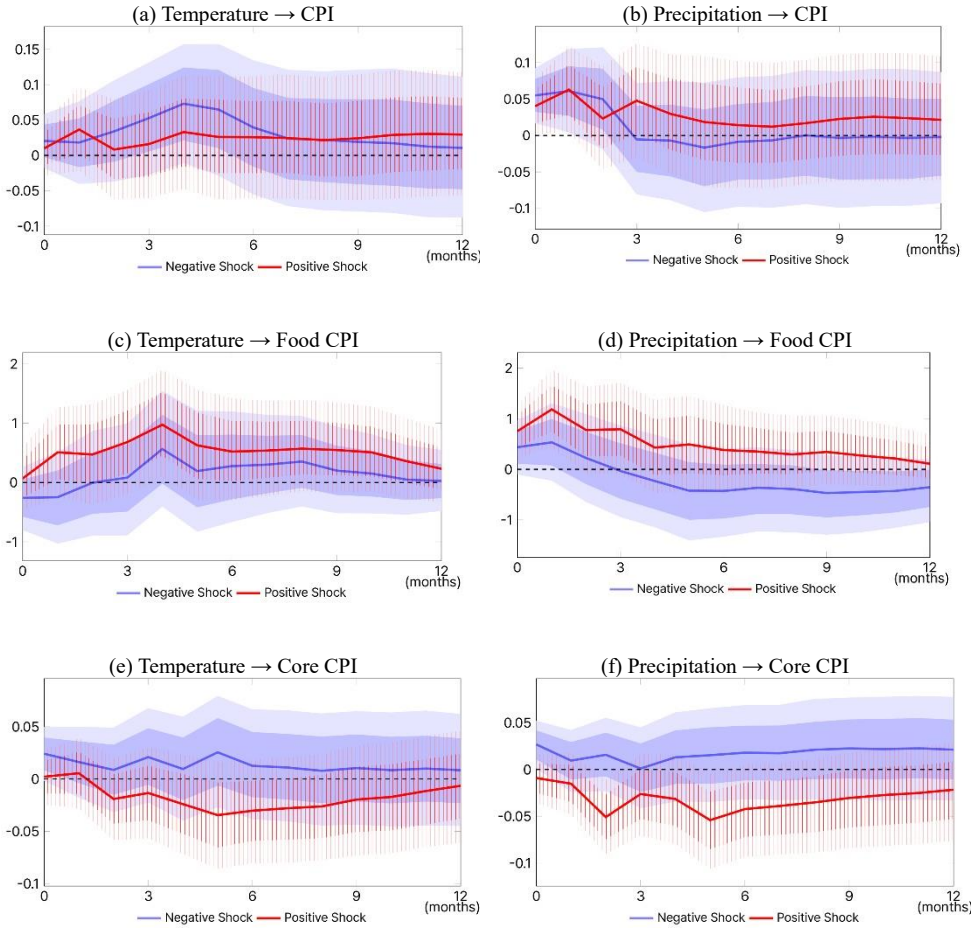


FIGURE C2. IMPULSE RESPONSES OF TEMPERATURE AND PRECIPITATION SHOCKS ON PRICES IN FALL

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light blue shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to negative weather shocks. Likewise, the dark and light red vertical lines indicate the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to positive weather shocks.

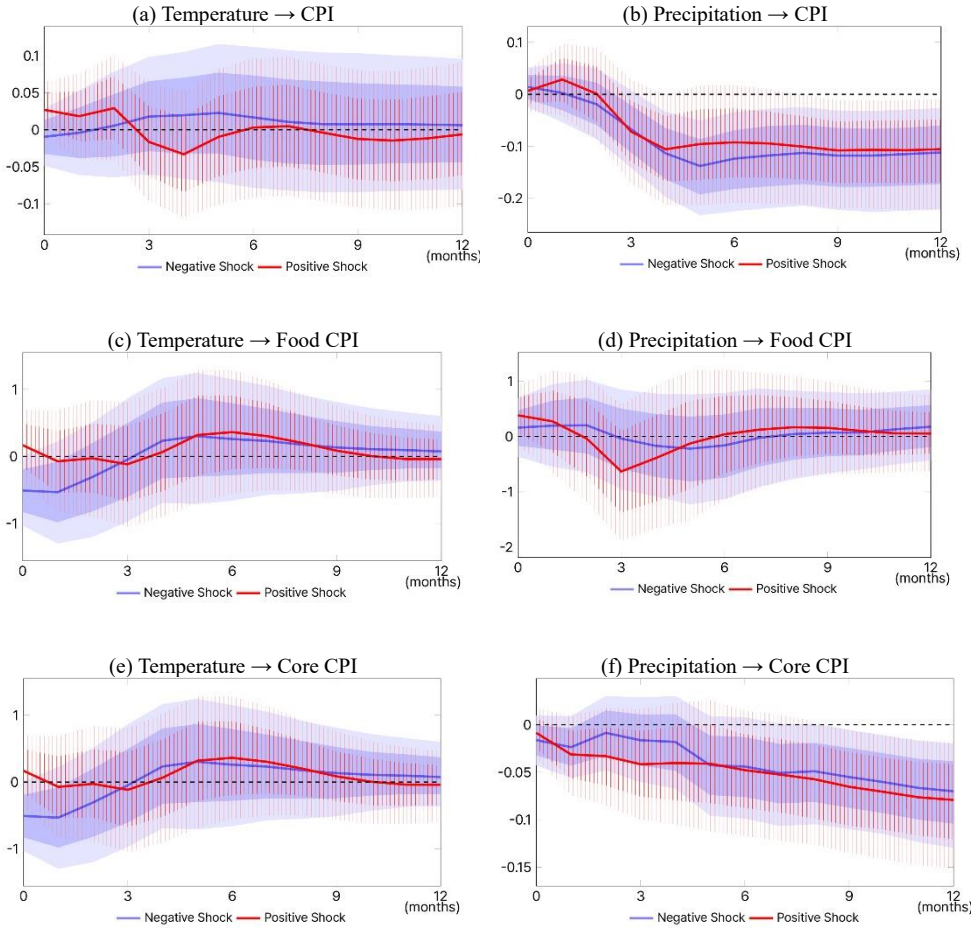


FIGURE C3. IMPULSE RESPONSES OF TEMPERATURE AND PRECIPITATION SHOCKS ON PRICES IN WINTER

Notes: Each panel in the figure presents the impulse responses of prices to weather shocks (temperature or precipitation). The dark and light blue shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to negative weather shocks. Likewise, the dark and light red vertical lines indicate the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to positive weather shocks.

D. *Impulse Responses of the Core CPI to Food CPI*

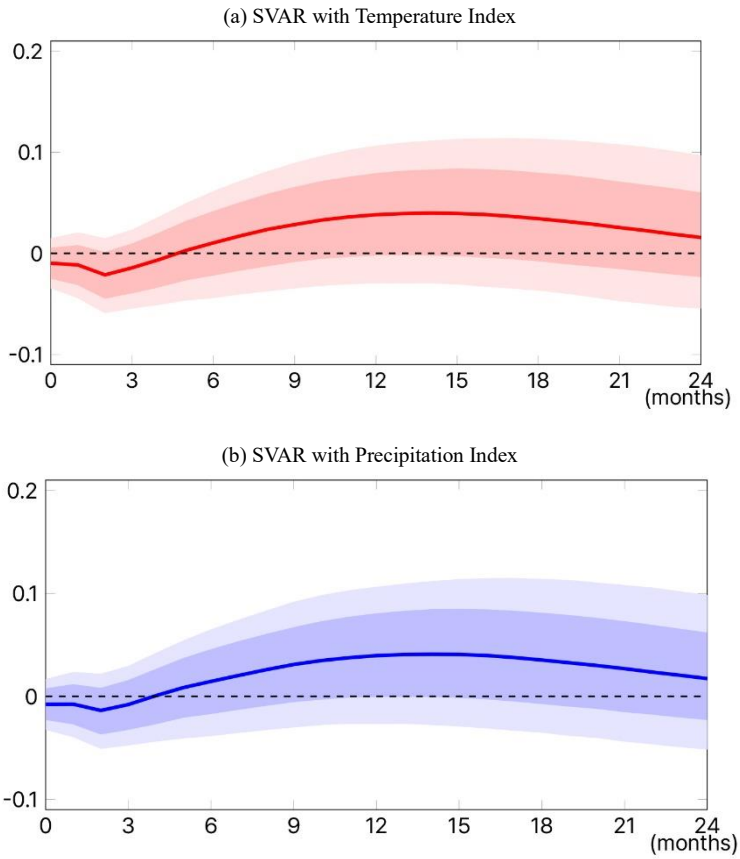


FIGURE D1. IMPULSE RESPONSES OF THE CORE CPI TO FOOD CPI

Notes: Each panel in the figure presents the impulse responses of the core CPI to food CPI shocks. The dark and light shaded areas represent the 68% and 90% bootstrap confidence intervals, respectively, for the impulse responses to food CPI shocks.

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