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The Impact of Climate Change on Inflation in the Kyrgyz Republic

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The Impact of Climate Change on Inflation in the Kyrgyz Republic

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List of Acronyms

1. **ADF** - Augmented Dickey-Fuller (test)
2. **ADW** - Angular Distance Weighting
3. **AIC** - Akaike Information Criterion
4. **ARIMA** - Autoregressive Integrated Moving Average
5. **BVAR** - Bayesian Vector Autoregression
6. **COP** - Conference of the Parties
7. **CPI** - Consumer Price Index
8. **CRU** - Climatic Research Unit
9. **CRU TS** - Climate Research Unit Time-Series
10. **FAO** - Food and Agriculture Organization (UN)
11. **FEVD** - Forecast Error Variance Decomposition
12. **GMM** - Generalized Method of Moments
13. **HICP** - Harmonized Index of Consumer Prices
14. **IPE-CSIC** - Pyrenean Institute of Ecology
15. **IRF** - Impulse Response Function
16. **KPSS** - Kwiatkowski-Phillips-Schmidt-Shin (test)
17. **LP** - Local Projections
18. **LR-tests** - Likelihood Ratio Tests
19. **M2** - Money Aggregate
20. **NBKR** - National Bank of the Kyrgyz Republic
21. **NER** - Nominal Exchange Rate
22. **NSC KG** - National Statistical Committee of the Kyrgyz Republic
23. **PDSI** - Palmer Drought Severity Index
24. **PET** - Potential Evapotranspiration
25. **PP** - Phillips-Perron (test)
26. **SDGs** - Sustainable Development Goals
27. **SPEI** - Standardized Precipitation-Evapotranspiration Index
28. **SPI** - Standardized Precipitation Index
29. **SVAR** - Structural Vector Autoregression
30. **SVARX** - Structural Vector Autoregression with Exogenous variables

Abstract

This paper empirically investigates the impact of climate-induced changes, represented by the Standardized Precipitation-Evapotranspiration Index (SPEI), on headline and food Consumer Price Indices (CPI) in Kyrgyzstan, with a focus on the agricultural sector as the transmission channel. The study employs Impulse Response Function (IRF) of the structural vector autoregression models with exogenous factors (SVARX), utilizing monthly data from 2000 to 2022.

The results show that drought shocks generate statistically significant and persistent inflationary effects, with food prices responding more strongly than headline CPI. A one-standard-deviation drought shock raises headline CPI by up to 0.8 percentage points and food CPI by up to 1.7 percentage points within nine months. The transmission operates mainly through reduced agricultural output, trade adjustments and exchange-rate depreciation.

Overall, from a policy perspective, having the short-term vulnerability to drought point to the importance of strengthening food supply stability, improving the capacity of trade to absorb shocks, and monitoring exchange rate dynamics to mitigate inflationary effects. Incorporating climate indicators such as the SPEI into inflation forecasting frameworks would enhance the accuracy and timeliness of policy responses.

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1. Introduction

Emissions of greenhouse gases into the atmosphere are the consequences of human activities that add extra heat to the climate system, leading to changes in climate. These changes, in turn, cause significant variations in weather conditions in the local, regional or global mean of temperature, humidity and precipitation patterns over the seasons, making countries and regions warmer, wetter or drier (World Bank Climate ChangeKnowledge Portal, 2021). The changes in climate also cause hazardous events, attributed as the acute risks[3] and increase their frequency and intensity in the decades to come.

In addition to acute hazards, the physical risks posed by the climate change also have a chronical (chronic risks) implication for the world economy through various transition channels. The exposure varying from country to country, the effect of gradual global warming on agriculture sector (prolonged drought affects the productivity of yields), energy demand, tourism, business, financial market and labour productivity can serve as an example (Cho, 2019).

Given the detrimental impact of climate change on global well-being, the mitigation of global warming has become a critical global priority. International efforts to combat climate change operate through frameworks such as the 2030 Sustainable Development Goals (SDGs), the Conference of the Parties (COP), and the Paris Agreement. Under the latter, participating nations commit to establishing Nationally Determined Contributions (NDCs), which are specific domestic mitigation measures and objectives. These national efforts, coupled with the strategic support of development institutions like the World Bank Group and the Asian Development Bank, demonstrate a unified global commitment to addressing the climate crisis. The goal is to restrict global warming to 1.5°C above pre-industrial levels by reducing global emissions. This transition to a lower-carbon world involves adopting and changing climate policies, technologies, energy systems, and market sentiment, which also gives rise to transition risks[4].

A review of the literature highlights the importance of addressing both physical and transition risks to effectively address climate change and its implications. Since accounting both risks necessitates identifying areas prone to hazards, assessing vulnerability and exposure, and subsequently implementing prevention, adaptation, and mitigation mechanisms.

Therefore, as climate change becomes more pressing, the assessment of climate risks has also attracted growing attention in recent years. In particular, there has been an increase in studies employing various approaches, including natural hazard–based climate risk assessments, scenario analyses of the impacts of changes in greenhouse gas concentrations, the deployment and development of low-carbon technologies, and shifts in policies and circumstances on subsequent temperature rises. However, it is surprising that there is little empirical research linking climate-induced changes, particularly in temperature and precipitation patterns, to key macroeconomic variables such as inflation. Furthermore, the majority of studies have focused on developed countries, with only a few conducted at the country level (Ciccarelli et al., 2023; Kotz

[3] The acute risks of the physical risks, such as excessive heat waves, wildfires, droughts, floods, mudflows, etc.
[4] Physical risk is the risk of economic and financial losses due to climate-related hazards;
Transition risk is the risk of financial losses related to regulatory and economic adjustments in a transition to a low-carbon economy (Cullen, 2023).

et al., 2023; Moessner, 2022).

A review of the existing literature revealed that developing economies are disproportionately vulnerable to climate change due to their heavy reliance on agriculture. However, the impact of changes in temperature and precipitation is ambiguous and varies across studies. Ciccarelli et al. (2023) argue that the effects of weather shocks on economic output and inflation are unlikely to be straightforward or linear. Instead, these impacts are influenced by a range of other factors, which could magnify or compound the impact of weather shocks.

These discrepancies attributed to significant differences in socioeconomic factors, technological advancements, ecosystem characteristics (including climatic conditions) and the level of exposure to hazards, vulnerability and capacities for mitigation and adaptation. The idiosyncrasies of each country raise questions about the applicability of existing research findings to other nations, as they may not be universally applicable. This emphasizes the need to conduct more country-level studies that consider these differences in order to gain more accurate insights.

In Kyrgyzstan's context, according to WBG and ADB reports, as well as a feasibility study carried out by UN agencies, suggest that the country's agricultural sector is already experiencing the effects of climate change, with projections suggesting further deterioration. The feasibility study by the UN agencies identified crop production as the most drought-sensitive sector of the Kyrgyz economy, with up to 30% of cropland potentially affected.

Given the significance and relevance of the macroeconomic implications of changes in temperature and precipitation patterns, and the conflicting findings regarding their impact on inflation, this paper aims to examine the effects of climate-induced changes, namely temperature and precipitation variations in the form of Standardized Precipitation Evapotranspiration Index (SPEI), on headline and food CPI in Kyrgyzstan.

Despite widespread recognition of climate change and its consequences, no prior research examining its effects on inflation or other macroeconomic indicators in Kyrgyzstan. Furthermore, considering the substantial dependence of the Kyrgyz economy on the agriculture sector[5], there is a growing need for an analytical framework that would acknowledge the National Bank of the Kyrgyz Republic (NBKR) and other interested parties about the impact of temperature and precipitation variation, if there is any, on the inflation through the agriculture transmission channel.

Thus, this paper utilizes monthly data from 2000 to 2022 on temperature and precipitation, in the form of SPEI index, as a proxy for climate variability, to investigate their relationship with headline and food CPI through the Impulse Response Function (IRF) of a Structural Vector Autoregressive (SVARX) model.

The study considers the agriculture sector as the primary transmission channel for the effects of changes in SPEI index and its conditions on inflation. The occurrence of drought throughout a year associates with the harming the yields of agricultural products, leading to higher food prices. Accordingly, this paper addresses the research question of whether drought conditions captured by the SPEI index exert a statistically

[5] The substantial dependence of the Kyrgyz economy on the agriculture sector, with approximately 18% of the economically active population directly engaged in this sector and as of 2022, it contributed to 11% of GDP – it further underscores the importance of this study (NSC).

significant positive effect on headline CPI and food CPI.

Accordingly, this study is guided by the following research question:

Research Question:

- Does drought, as measured by the Standardized Precipitation Evapotranspiration Index (SPEI), have a statistically significant effect on consumer price index (CPI) in Kyrgyzstan?

Based on the literature and the country's reliance on agriculture, the study advances the following hypothesis:

Hypothesis:

- *H_1: Drought conditions (negative SPEI values) exert a statistically significant positive effect on CPI through the agricultural transmission channel.*

The empirical analysis includes headline CPI (inflation), food CPI, total grain crop yields, money aggregate (M2), import and export volumes, the output gap, administrative prices, and the nominal exchange rate (NER). These domestic macroeconomic variables were sourced from publications of the NBKR.

External price indicators, specifically the FAO global food price index and the consumer price indices of Kazakhstan and Russia, were obtained from the respective official statistical authorities.

Climate variables, including temperature and precipitation data used to construct the SPEI, were sourced from the Climatic Research Unit (CRU).

The remainder of the paper is structured as follows: Section 2 presents a selective review of the literature on the impact of temperature and precipitation variations on inflation. Section 3 reviews the agricultural sector, highlighting its role as the transmission channel between climate shocks and inflation. Section 4 describes the data and methodology, while Section 5 presents the results and discussion section. Section 6 concludes the paper.

2. Literature review

The relationship between weather shocks and inflation (or economic output) is complex and influenced by multiple variables, rather than being solely determined by changes in weather conditions. The study by Ciccarelli et al. (2023) suggests that the effects of weather shocks on economic output and inflation are probably not straightforward or linear. Instead, they are likely influenced by various other factors, which could magnify or compound the impact of weather shocks. This paper assessed the impact of weather shocks on inflation components in the four largest euro area economies, using monthly data and Bayesian Vector Autoregressions models to account explicitly for seasonal dependence. The results obtained show that an increase in the monthly mean temperature raises inflation the most in summer and partly in autumn, with a stronger response in the warmer euro area countries. Thus, when the shock occurs in summer, the responses of inflation rates to a 1◦C deviation of monthly temperature from its historical mean for Germany, France, Italy, and Spain led to an increase in inflation of between 0.1 and 0.2 p.p. in the first year. According to the authors, the decline in agricultural productivity was a possible transmission channel through which the shock led to an inflationary effect. However, the overall impact of the weather shock was mixed, depending on the temperature shock itself, whether it was a warm or cold spell, the seasons, the components of the Harmonized Index of Consumer Prices (HICP) and the general cold or warm temperature characteristics of the countries.

Similarly, the research by Rodrigues et al. (2024) found the complexity and heterogeneity of the effect of climate change on consumer prices (inflation). The effects were measured by impulse response functions (IRFs) derived from Local Projections (LP) using data from 2001 to 2020, including averages of monthly inflation rates, climate data (temperatures, precipitation, wind speed, and solar radiation), producer prices of the sector, euro area commodity prices, and industrial production of 20 euro area countries (averaged). The results of the research provided granular results, leading to the conclusion that the impact varies across regions and sub-sectors depending on the size of countries and climate zones, various weather variables with differing magnitudes and signs, and seasons.

Another ECB working paper by Kotz, Kuik, Lis, and Nickel (2023) also highlighted agricultural productivity losses as one of the two major channels (the second one is labor productivity) and conducted empirical estimates of historical climate impacts on inflation, combining them with state-of-the-art physical climate models to estimate the implications for inflation from projected future warming. The impact of rising average temperatures in higher- and lower-income countries was found to be non-linear but persistent. However, temperature increases in hotter months and regions lead to larger increases in inflation, while temperature increases in the coldest months were mostly not tangible. Another climate variable examined by the authors is exposure to abnormal precipitation conditions and its impact. Using the SPEI index, the study found that excess wet conditions have an upward impact on inflation that persists over twelve months, while excess dry conditions have some significant upward impacts when they occur in hot months or regions, but these are generally less persistent or significant. Projections from state-of-the-art climate models depicted that future warming will increase global annual food and headline inflation by 0.92-3.23 and 0.32-1.18 p.p. per year, respectively, by 2035.

Cevik (2023) conducted an empirical analysis of the impact of climate shocks (temperature, drought shock, etc.) on inflation in a sample of 173 countries over the period 1970-2020. The results show significant variation of transmission channels depending on the level of economic development and diversification across countries[6]. IRFs using the LP method led the authors to conclude that a temperature shock leads to a sustained increase in headline inflation in advanced economies, while it has the opposite effect in developing countries. In the case of a drought shock, headline inflation rises above the initial level in the first year and over the long run, but this effect is small and disappears quickly in advanced economies compared to developing countries where it is long-lasting. According to authors, such differences in the magnitude and pattern across country groups of the impact of weather-related shocks on core and food inflation are due to their non-linearity, depending on the state of the economy and the degree of fiscal space at the time of the shock. One of the transition channels identified by authors, which varies significantly with the level of economic development and diversification across countries, is agriculture production, leading to different impacts across country groups that increase or decrease agricultural production and food prices.

Mukherjee and Ouattara (2021) investigated the impact of climate change on inflation for a panel of developed and developing countries over the period 1961–2014. Using a panel VAR model, the results suggest that climate change leads to inflationary pressures in both developed and developing countries that persist for several years after the initial shock. The results of the IRFs for a combined sample of developed and developing groups show that a 1% change in temperature significantly increases inflation by 2.6, which persists up to 4 years after the initial shock and slowly declines. Taking into account the homogeneity across countries in the sample, the authors split the sample into developed and developing countries and ran the IRFs. The response of inflation for developed countries to a 1% change in temperature was positive and statistically significant, increasing by around 2.4% and decaying after one year, while the IRFs for developing countries lead to an increase in the inflation rate of about 2.7%, which remains significant up to 6 years after the initial shock.

The varying results were even obtained among the developing countries of the same region. Köse and Ünal's (2022) study on the temperature effect on food inflation uses a structural VAR model and panel Granger causality test, using monthly data between 2003 and 2020 for Latin American countries. It is worth noting that the economies of the selected countries are developing, and a large part of their exports consist of agricultural products. The study revealed mixed results across the countries; the IRFs to structural one-standard-deviation positive innovation were not statistically significant for Argentina, Colombia, Ecuador, Uruguay, and Mexico, while only for the Dominican Republic it was positive and statistically significant in the first two months. In addition, the variance decomposition for Argentina showed an effect of maximum 2.5% in the 12th month, for the Dominican Republic the effect of the temperature change increased from 2.3% to 6.9% between the first and the 12th month, for Uruguay it was around 6.5% in the 12th month, while for Ecuador and Mexico the changes in temperature turned out to be the highest determinant with an explanatory power of 8.6% and 9.0% respectively. However, changes in temperature in the variance

[6] The extreme temperatures defined by authors as "a general term for temperature variations above (extreme heat) or below (extreme cold) normal conditions and droughts as "an extended period of unusually low precipitation that produces a shortage of water for people, animals and plants".

decomposition for Colombia, temperature changes were not a significant explanatory factor for food inflation. Finally, the Granger causality test also indicated that temperature changes do not Granger cause food inflation, as these tests fail to reject the null hypothesis at the 5% significance level for all countries.

Another study on the impact of rainfall and temperature on core and food CPI (inflation) was conducted by Odongo et al. (2022) for countries in Eastern and Southern Africa. They used GMM for dynamic panel data to address the endogeneity problem using monthly data for the period 2001 and 2020. The results show that the temperature variability variable is positive but statistically significant only for the CPI of basic commodities but not for the CPI of food. Rainfall variability is also positively correlated with core and food inflation and is statistically significant. In addition, the third variable, the monthly average temperature variable, was found to be statistically significant but with a negative sign. According to the authors, a possible explanation for the fact that the effect of temperature volatility is positive and significant only for core inflation, but not for food inflation, is explained by the possible impact of temperature volatility not only on food, but also on other components of the consumer basket. In particular, on electricity, the prices of which rise with the increase in production costs. The authors' explanation for the negative and statistically significant effect of rainfall variability on headline and food inflation is that high rainfall leads to lower food prices and lower inflation, as higher rainfall increases overall agricultural productivity. Finally, rainfall variability leads to changes in the amount and timing of rainfall within the season, which reduces agricultural supply, including food, leading to high food prices and headline inflation.

The research that studied a country-level empirical research is very few. The study by Yusifzada (2022) is one of the few that analyzed the impact of temperature changes on the long-term inflation trend in Azerbaijan. It used data from 2005 to 2020 and forecast annual inflation for the period 2021-2030 using the Bayesian VAR model. Two scenarios were considered: the normal scenario, in which the temperature increases to 13.8°C and with 415.6 mm of total annual precipitation, and the worst-case scenario, in which the temperature increases to 15°C and precipitation decreases to 395.6 mm. To obtain the projections under the normal scenario, the Autoregressive Integrated Moving Average (ARIMA) model was used to project the trends of the variables for the period 2021-2030. The Bayesian VAR model was then used to assess the response of inflation to temperature changes under the worst-case scenario. The results indicated a potential increase in inflation of 2.1 percentage point (p.p.) by the end of 2030 under the adverse scenario, which is 1.2 p.p. higher than under the normal scenario. It is important to note that these scenario-based results took into account transition risks resulting from lower-carbon policies that could affect fuel revenues – a key aspect of Azerbaijan's economy. According to the author, climate change affects not only seasonality but also long-term inflation trends. Consequently, the study recommends the implementation of a comprehensive climate action plan, including monetary incentives, to facilitate the transition to a green economy.

The review of the above literature indicates the possible impact of climate change on inflation, although the magnitude and nature of this effect depend on a variety of factors. The findings diverge across country groups mainly due to geographical location (including ecosystems and climate conditions) and the state of their economies. These differences also alter the transmission channels of influences on inflation, suggesting that the agricultural sector for developing countries appears to be a common transmission channel through which inflation in these countries is affected by climate variability. This relationship also explains why increases in temperature during the agricultural grown period is most likely to affect the inflation rate, which is mainly what the reviewed studies found, although it was also significant for some developed countries.

The literature further reveals variations in the measurement of climate variables: temperature has been expressed using SPEI, average values, or threshold-based indicators, while precipitation has been captured through absolute averages, volatility measures, or anomalous values.[7] Overall, the vast majority of studies find that these climatic changes affect inflation, with only a few reporting no significant effect.

Moreover, country-level empirical studies are scarce, and none have focused on Kyrgyzstan. This highlights the relevance of examining the potential impact of temperature and precipitation changes, particularly in SPEI form, on inflation in the Kyrgyz context.

[7] The overall literature review highlighted the potential impact of climate change shocks, in this case changes in temperature and precipitation patterns. This review did not consider other related studies, such as the impact of natural disasters (acute risk) or changes in policy, technology or other risks arising from transition risks. Additionally, the impact of climate change on other macroeconomic indicators was excluded, as their consideration was not relevant or necessary.

3. Agriculture Sector as a Climate Change Transmission Channel

The agricultural sector is considered in this paper as a transmission channel for climate change. The Kyrgyz economy relies heavily on agricultural sector, with approximately 18% of the economically active population directly engaged in it, while the share of the total population involved in agriculture constitutes 60% of the overall population. Moreover, as of 2022, the sector contributed 11% to the country's GDP (NSC KG, 2023).

According to the NSC, the main agricultural products grown in Kyrgyzstan includes cereals (wheat, barley and corn), potatoes and vegetables. In 2022, total harvests amounted to 1,867.3 thousand tonnes of cereals, 1,275 thousand tonnes of potatoes, and 1,163.6 thousand tonnes of vegetables (see Table 1 for details). This production is generally sufficient to meet domestic demand for the typical "consumer basket" of agricultural products, with the exception of bread products, as about half of the wheat consumed is imported from Kazakhstan.

Table 1: Production of Main Agricultural Products in the Kyrgyz Republic (thousand tonnes)

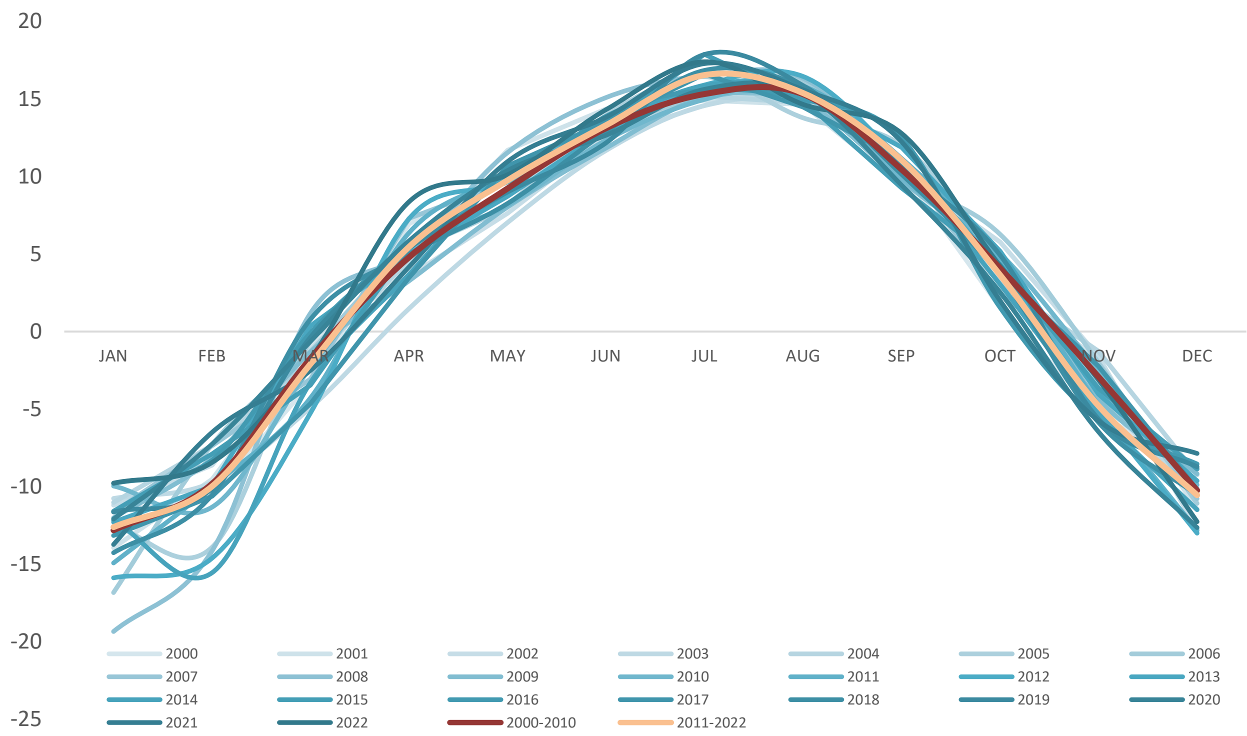
Products	**2019**	**2020**	**2021**	**2022**	**2023**
Grains (weight after reprocessing)	1781.4	1856.0	1329.1	1867.3	1623.8
Wheat (weight after reprocessing)	601.2	629.1	362.7	592.5	440.4
Barley (weight after reprocessing)	465.9	510.2	274.0	539.6	382.1
Corn	711.8	714.1	691.1	732.6	799.9
Rice (weight after reprocessing)	41.2	44.5	46.3	44.2	46.8
Leguminous (weight after reprocessing)	108.6	107.2	85.5	80.7	72.3
Including beans	102.5	103.6	82.6	78.3	69.9
Sugar-beet (fabric)	741.1	448.8	365.6	468.1	621.0
Cotton (at recorded weight)	80.2	72.8	66.9	76.5	63.5
Potatoes	1373.8	1327.2	1289.1	1275.0	1286.8
Vegetables	1133.6	1131.2	1114.1	1163.6	1216.6
Melons	245.8	261.5	224.9	226.1	235.6
Fruits and berries	269.5	278.0	266.4	275.5	278.9

According to reports by the World Bank Group (WBG) and the Asian Development Bank (ADB), as well as a feasibility study conducted by UN agencies, Kyrgyzstan's agricultural sector is already experiencing the effects of climate change, with projections indicating further deterioration. The Climate Risk Profile: Kyrgyz Republic (2021) report highlights that average annual agricultural losses due to hazards between 1991 and 2011 amounted to at least 14 million USD, primarily caused by drought and water scarcity. Similarly, the UN feasibility study identified crop production as the most drought-sensitive sector of the Kyrgyz economy, with up to 30% of cropland potentially affected.[8]

[8] According to report by WBG and ADB, the Kyrgyz Republic is vulnerable to two types of drought: (1) meteorological usually associated with a precipitation deficit and (2) hydrological usually associated with a deficit in surface and subsurface water flow, potentially originating in the region's wider river basins.

Analyses of data on temperature, precipitation and major agricultural products showed results consistent with the above-mentioned studies. Starting with temperature, Figure 1 illustrates the changes in seasonal average temperatures over the period 2000-2022. The data show that average autumn and winter temperatures in Kyrgyzstan decreased by 1.7°C and 0.26°C, respectively, during the period 2011-2022 compared to the period 2000-2010, and conversely increased in spring and summer by about 0.84°C and 1.5°C (see Figure 1 for details).

Figure 1: Historical Monthly Average Daily Temperature for Kyrgyzstan from 2000 to 2022

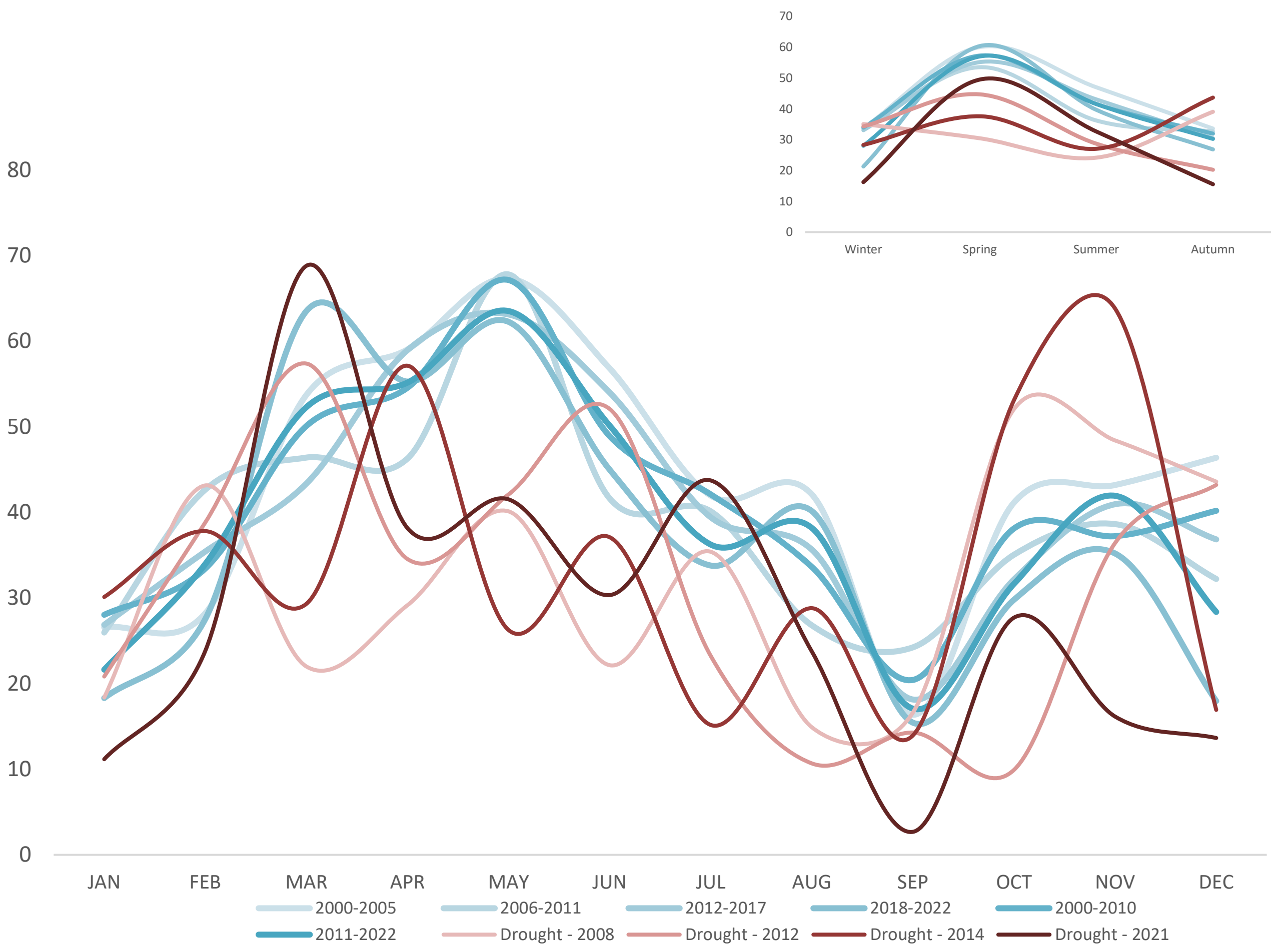


Author's own calculations.

Regarding changes in precipitation patterns, the seasonal mean precipitation decreased in all seasons between 2000-2010 and 2011-2022 (refer to Figure 2 for illustration). The most significant decrease occurred in winter, from approximately 29 millimeters (mm) to 16 mm, while in other seasons the decrease was about 1 mm. In addition, as can be seen, Kyrgyzstan experienced four countrywide droughts in 2008, 2012, 2014 and 2021.

During these drought years, precipitation fell in almost all seasons, with some minor exceptions (refer to Figure 2). Of particular note is the significant decrease in summer precipitation, with the lowest recorded being 24 mm in 2008, a decrease of about 42% compared to the average seasonal precipitation of 2011-2022 (normal). In 2021, summer precipitation was 32 mm, which was 5 mm higher than the previous droughts, but about 9 mm lower than the average seasonal precipitation of 2011-2022. Spring precipitation in the 2021 drought averaged 49 mm, also higher than in previous droughts, but about 7 mm below the norm. In contrast, winter and autumn precipitation in 2021 reached record lows of 16 mm and 15.5 mm respectively, about half the amount of previous droughts and the norm.

Figure 2: Historical Monthly Average Daily Precipitation for Kyrgyzstan from 2000 to 2022

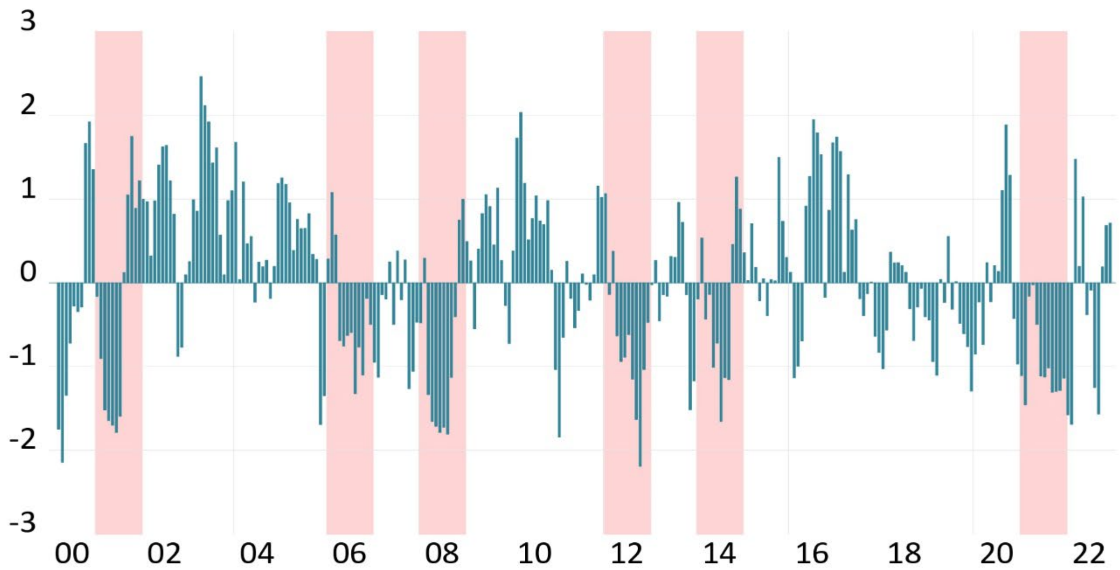


Author's own calculations.

Alternatively, using the conjunction of temperature and precipitation data, as well as soil moisture and evapotranspiration factors, the SPEI, a drought index that measures drought severity by considering both intensity and duration, can be obtained (more details on the calculation and method of the SPEI index are in the next section). Figure 3 illustrates the monthly drought index from 2000 to 2022. As shown, the obtained SPEI index aligns with the overall changes in precipitation and temperature data discussed above. The index also indicates that extreme drought conditions occurred 4 times during this period. Kyrgyzstan experienced severe droughts in 2008, 2012, 2014, and 2021 due to both high intensity (SPEI index surpassing -1) and long duration (drought conditions persisting throughout most months of the year).[9]

[9] Additionally, the years 2001 and 2006 can be considered drought years. In 2001, drought conditions were mainly characterized by their intensity, with an average SPEI of -1.5 from February to July. Meanwhile, in 2006, this classification is primarily due to the prolonged duration of drought conditions from April to December.

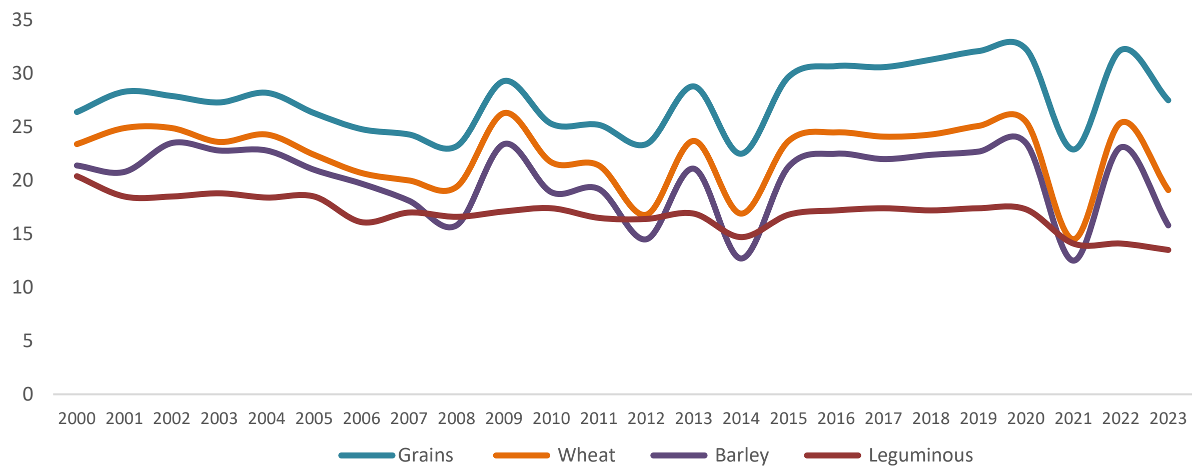
Figure 3: Historical Monthly SPEI Index for Kyrgyzstan from 2000 to 2022



Author's own calculations. The SPEI is calculated using precipitation and the climatic water balance (difference between precipitation and potential evapotranspiration (PET)) over 3-month accumulation periods. Author's own computation via Windows console developed by CSIC (2009), at the three months accumulated interval.

The impact of these droughts is evident in Table 1, showing significant reductions in cereal crop yields – about 27% lower than the average of the preceding two years. Figure 4 presents yields per hectare for wheat, barley, and grain legumes, highlighting the declining trend during drought years. For example, cereal yields per hectare fell by 0.9 quintals (4.5%) in 2008, 2.2 quintals (7.1%) in 2012, 6.6 quintals (21.9%) in 2014, and 9.4 quintals (29.0%) in 2021. If this trend continues, future droughts could lead to yield reductions exceeding 30%.

Figure 4: Grain Crop Yields per Hectare in Kyrgyzstan (2000-2023)



Author's own calculations

Apart from the impact of drought, the impact of changes in temperature and precipitation patterns, represented by SPEI index, on agricultural products is not clear and not much can be said on the basis of descriptive analysis. In addition, the precise importance of SPEI index for the agricultural sector and the wider economy remains poorly understood. Similarly, the effect of these climatic changes on inflation has yet to be thoroughly studied.

Given the central role of agriculture in Kyrgyzstan's economy and the influence of climate variability on production, the sector is considered the primary transmission channel for climate-induced shocks to CPI. The proposed framework illustrates this mechanism: droughts captured by the SPEI reduce grain crop yields, which increase food prices and exert upward pressure on food CPI. This effect may further propagate indirectly to headline CPI through macroeconomic channels, including money aggregate (M2), trade volumes (imports and exports), and the nominal exchange rate (NER), which can amplify or mitigate the inflationary impact. The framework thus emphasizes both the direct role of agriculture and the indirect influence of key macroeconomic variables in linking climate variability to inflation.

4. Methodology and data description

4.1. Macroeconomic variables

This paper uses monthly time series data for Kyrgyzstan over the period 2000–2022. The macroeconomic variables included in the analysis are:

- FAO Food Price Index (FAO)
- Headline CPI of the Republic of Kazahkstan (CPI_KAZ)
- Headline CPI of the Russia (CPI_RUS)
- Administrative Prices (ADM_PRICES)
- Total yields of grain crops (GRAIN_CROPS)
- Money aggregate (M2)
- Nominal Exchange Rate (NER)
- Volume of imports (IMP) and exports (EXP)
- GPD gap (GDP_GAP)
- Headline Consumer Price Index (CPI) and Food CPI (Food_CPI)

All macroeconomic variables were obtained from the NBKR bulletins, except for the FAO index, which was sourced from the FAO website, CPI rate of Kazakhstan sourced from National Bank of the Republic of Kazakhstan and CPI rate of Russian from Central Bank of the Russian Federation. The selection of variables was guided by economic theory, institutional knowledge, and prior research, reflecting key channels through which climate-induced shocks may affect inflation.

The headline CPI and food CPI of Kyrgyzstan, the GDP gap, the CPI of Kazakhstan, the CPI of Russia, and administratively regulated prices measured as month-on-month national-level rates. Trade data, comprising imports and exports are measured in millions of USD, while the money aggregate is in millions of Kyrgyz Soms. These variables and the nominal exchange rate than transformed into growth rates.

Prior to estimation, all variables (except grain crop yields) are transformed into cumulative series and seasonally adjusted using the X-13 seasonal adjustment procedure implemented in EViews. The seasonally adjusted series are then expressed in natural logarithms and scaled by 100. Finally, the variables retransformed into growth-rate form.

For the analysis of grain crop yields in Kyrgyzstan, annual production data in tonnes were obtained from the NSC. To create a monthly series, the annual yields were divided and equally distributed from June to October (harvest months) according to the grain crop calendar (USDA FAS, IPAD), while non-harvest months were set to zero to reflect true zeros. To stabilize the variance and reduce skewness, the series was log-transformed using $\ln(1 + y_{t,m})$, which allows for the inclusion of zero values. Although this approach assumes equal monthly allocation during the harvest season, it is appropriate for the analysis, as the main economic and policy relevance lies in total annual production rather than intra-seasonal variations. Therefore, this procedure preserves the primary information of interest.[10]

In addition, several dummy variables were introduced to account for exceptional spikes during periods of economic or political shocks, as well as month dummies to control for seasonality. These variables were

[10] Important to note that the total yields of grain crops is used only as a proxy for agricultural sector productivity and was not intended to represent the agriculture sector as a whole.

included in the exogenous section of the model.

4.2. Climatic indicators

The climatic variables are obtained from World Bank Data Knowledge Portal, which sourced the data from Climatic Research Unit of the University of East Anglia. Climatic Research Unit gridded Time series (CRU TS) is a widely used dataset on a 0.5 latitude by 0.5 longitude grid of a high-resolution monthly grid of land-based (except for Antarctica) observation from 1901 and yearly updated to present. The data are monthly gridded fields based on monthly observational data calculated from daily or sub-daily data by National Meteorological Services and extensive networks of weather station observations using angular-distance weighting (ADW) interpolation. The dataset contains ten variables classified as primary, secondary and derived variables. In this study, the primary variables, namely actual average monthly mean temperature and aggregated monthly-accumulated precipitation values over the aggregation period were used, which is from CRU TS 4.07 0.5 - degree release. The CRU TS 4.07 release covers the period 1901-2022.

These variables were transformed into the Standardized Precipitation-Evapotranspiration Index (SPEI) form to assess the SVARX model's IRFs.[11] The SPEI, a new drought index developed by the Pyrenean Institute of Ecology (IPE-CSIC) in Zaragoza, Spain, measures drought severity, considering both its intensity and duration. The SPEI calculated using precipitation and the climatic water balance (difference between precipitation and potential evapotranspiration (PET)) on *i*-month accumulation periods.[12] For this study, the index obtained via program executed from the Windows console developed by CSIC (2009), at the three months accumulated interval, using monthly time series of precipitation and mean temperature, as well as the geographic coordinates of the observatory. From the obtained SPEI variable, only the drought conditions were used to trace their impact on headline and food CPI.

[11] The SPEI index is similar to other widely used indices such as the Standardised Precipitation Index (SPI) and the Palmer Drought Severity Index (PDSI). However, the SPEI employs a simpler statistical approach compared to the PDSI, which considers factors such as precipitation, temperature, soil moisture, and evapotranspiration. Additionally, the SPEI incorporates potential evapotranspiration (PET) in addition to precipitation, whereas the SPI relies solely on precipitation data.

[12] PET represents the amount of water that could be lost to the atmosphere through evaporation from surfaces like soil and transpiration from plants if there were enough water available for these processes to occur.

4.3. Stationarity Tests and Model Diagnostics

Augmented Dickey-Fuller (ADF), Philips-Perron (PP), and Kwiatkowski-Philips-Schmidt-Shin (KPSS) unit root tests conducted on the series to assess stationarity. All tests resulted that the series are stationary. The lag length criteria based on the Akaike Information Criterion (AIC), which suggested the inclusion of 12 lags, including 12 lags in both models satisfied the diagnostic tests.

To ensure the robustness and reliability of the obtained results, a series of diagnostic tests were conducted. However, due to the dimensionality of the system and the imposition of block-exogeneity, some multivariate residual diagnostics tests are computationally unstable when applied directly to the restricted VARX. The residual diagnostic such as serial correlation and heteroscedasticity are therefore conducted on the corresponding unrestricted VAR. Stability conditions and likelihood-ratio tests for over-identifying are evaluated on the restricted specification. The results indicate that the models are dynamically stable and that the imposed restrictions are consistent with the data.

4.4. Model description

To analyze the effects of drought shocks on domestic inflation dynamics, the paper relies on economic theory and empirical evidence to construct a Structural VAR with exogenous variables (SVARX). Drought conditions are measured using the Standardized Precipitation–Evapotranspiration Index (SPEI), which captures deviations in climatic water balance and is treated as a purely exogenous climatic process.

The empirical framework adopts a restricted VARX specification to examine the impact of drought on headline and food inflation, as well as on key macroeconomic and trade variables[13]. The systemis estimated using monthly data and includes 12 variables.

The reduced-form VARX representation is given by:

$$z_t = \sum_{i=1}^{p} \Phi_i \, z_{t-i} + \phi d_t + e_t \qquad (1)$$

where:

- z_t is an $N \times 1$ vector of variables at time t,
- d_t[14] represents the deterministic components (seasonal and event dummies)
- e_t is the vector of reduced-form residuals

To reflect the theoretical independence of global and climate factors and impose block-exogeneity restrictions on the coefficient matrices Φ_i the system vector partitioned as:

$$z_t = [s_t, x_t, w_t, y_t]$$

Specifically, the drought block (s_t) and the exogenous block (x_t) are restricted to depend only on their own past values, similarly the partially exogenous block (w_t) restricted to depend on their own past values and also influenced by s_t, while the endogenous block (y) is influenced by the lags of all variables in the system.

- s_t is a vector of SPEI_drought

$$s_t = \sum_{i=1}^{p} \Gamma_i \, s_{t-i} + e_{s,t}$$

- x_t is a vector of exogenous block, where each x-variable depends only on its own past values at lag one (own-lags-only restriction):

$$x_t = \sum_{i=1}^{p} \gamma_i \, x_{t-i} + \phi_x d_t + e_{x,t}$$

[13] To this end, the paper employs two models that are similar to each other: one for headline CPI, and the second for food CPI, so to compare the obtained results.

[14] Three dummy variables for geopolitical events and a variable for NBKR interventions were included, appearing only in the equation for the Nominal Exchange Rate (NER).

with:

- global food prices (FAO);
- CPI of Kazakhstan;
- CPI of Russia;
- Administrative prices (cpi_adm).

- w_t is a vector of partially exogenous block:

$$w_t = \sum_{i=1}^{p} \delta_i \, w_{t-i} + \sum_{i=1}^{p} \theta_i \, s_{t-i} + \phi_w d_t \; + e_{w,t}$$

including:

- total yields of grain crops;
- imports;
- exports.

- y_t is the vector of endogenous variables, including:

$$y_t = \sum_{i=1}^{p} A_i \, y_{t-i} + \sum_{i=1}^{q} \Gamma_i \, s_{t-i} + \sum_{i=1}^{p} \gamma_i \, x_{t-i} + \sum_{i=1}^{p} \delta_i \, w_{t-i} + \phi_y d_t \; + e_{y,t}$$

where:

- headline CPI/food CPI;
- nominal exchange rate (NER);
- Money aggregate (M2);
- GDP gap.

For estimation purposes, the model is expressed compactly as:

$$z_t = B_1 x_{t-1} + e_t \qquad (2)$$

where x_{t-1} includes all lagged z_t and deterministic components, and B_1 is an $N \times K$ restricted coefficient matrix (K is the total number of variables in x_t). e_t is an $N \times 1$ vector reduced-form residuals, with variance-covariance matrix. $\sum_e = E(ee')$.

To identify contemporaneous effects and structural shocks, the VARX can be expressed in structural form:

$$A_0 z_t = A_1 x_{t-1} + \varepsilon_t \qquad (3)$$

where A_0 is an $N \times N$ matrix capturing contemporaneous interactions among variables, $A_1 (A_0 B_1)$ is an $N \times K$ coefficient matrix linking lagged endogenous and exogenous repressors x_{t-1} to the structural equations of the system, ε_t is an $N \times 1$ vector of structural shocks/innovations, assumed to be “orthogonal” (uncorrelated) to one another, such that:

$$E[\varepsilon_t \varepsilon_t'] = \Sigma_\varepsilon = diag(\sigma_1^2, \dots, \sigma_N^2).$$

Reduced-form residuals e_t are related to structural shocks by:

$$e_t = A_0^{-1}\varepsilon_t, \;\; \sum_e = A_0^{-1}\Sigma_\varepsilon\,(A_0^{-1})'.$$

In case of leaving A_0 free (unnormalized form), the SVARX models can be written as:

$$Az_t = A_1 x_{t-1} + B\eta_t \tag{4}$$

where A=A_0, $A_1 = B_1 A_0$, and η_t denotes normalized structural shocks with unit variance, and B is diagonal and contains the standard deviations of the structural shocks. The relationship between normalized and unnormalized shocks is given by $\varepsilon_t = B\eta_t$.

Substituting the reduced-form VARX into equation (4) yields:

$$A(B_1 x_{t-1} + e_t) = A_1 x_{t-1} + B\eta_t \tag{5.0}$$

which after the cancellation of terms demonstrates the link between reduced-form residuals and structural shocks:

$$Ae_t = B\eta_t \tag{5.1}$$

For IRF analysis it is convenient to get structural shocks that are normalized to unit variance η_t (unit variance), which get the from:

$$\eta_t = D^{-1}\varepsilon_t, \text{ or } \eta_t = B^{-1}Ae_t, \;\; D = diag(\sigma_t) \tag{5.2}$$

where D contains the standard deviations of the shocks.

Further, the model requires the identification of the matrices A and B in order to recover structural shocks for impulse response analysis. The system includes n = 12 variables, all incorporated in a recursive ordering according to their level of exogeneity. The reduced-form VARX provides $n(n+1)/2$ = 78 unique elements in the residual covariance matrix Σ_e.

In the structural SVARX model, the A matrix contains n^2- n = 132 potential free elements. To achieve identification, we impose 66 zero-restrictions on the upper-triangular elements and 10 zero-restrictions on the lower-triangular of A via a recursive (Cholesky) ordering. Additionally, because the autoregressive coefficient matrix B_1 was previously restricted in the reduced-form stage (imposing block-exogeneity), the total number of restrictions exceeds the minimum required for identification, resulting in an over-identified system. This over-identification is tested using a Likelihood Ratio (LR) test to ensure the structural model remains consistent with the data.

The imposed restrictions on the matrices A and B (normalized) are designed to capture two types of identification constraints: behavioral restrictions on A, and restrictions linked to the impulse-response structure on B. These restrictions are imposed according to a recursive ordering of the variables. Because the shock applied to the SPEI variables must reflect the key characteristics of climatic shocks, they are treated as exogenous with respect to all other contemporaneous and lagged variables in the model.

Accordingly, SPEI drought is placed first and allowed to respond only to its own shock, under the assumption that a shock to SPEI drought affects the other variables contemporaneously and with lags. While the index itself does not respond to shocks from other variables within the same period. Following SPEI, the FAO index, the CPI of Kazakhstan, CPI of Russia and Adm_prices are placed next in the ordering. They are assumed to contemporaneously affect all other variables (except SPEI drought and grain crop outputs) but do not respond contemporaneously to those same variables.

Subsequently, GRAIN_CROP, IMP, EXP, NER, M2, and the GDP gap are ordered to capture the direct and indirect effects of SPEI shocks on agricultural, trade, and macroeconomic activity. Finally, CPI and Food_CPI are placed at the end of the ordering, reflecting the assumption that these price indices respond contemporaneously and with lags to all other variables in the system, thereby capturing both immediate and delayed price effects.

Thus, this ordering is consistent with the idea that shocks propagate through the economy in a sequential manner, with some variables responding immediately to certain shocks while others respond indirectly through subsequent channels.

Subsequently, the *A* and *B* of the recursive SVARX is over-identified and given as:

$$Ae_t = \begin{bmatrix} NA & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & NA & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & NA & NA & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ NA & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ NA & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ NA & NA & NA & NA & NA & NA & 1 & 0 & 0 & 0 & 0 & 0 \\ NA & NA & NA & NA & NA & NA & NA & 1 & 0 & 0 & 0 & 0 \\ NA & NA & NA & NA & NA & NA & NA & NA & 1 & 0 & 0 & 0 \\ NA & NA & NA & NA & NA & NA & NA & NA & NA & 1 & 0 & 0 \\ NA & NA & NA & NA & NA & NA & NA & NA & NA & NA & 1 & 0 \\ NA & NA & NA & NA & NA & NA & NA & NA & NA & NA & NA & 1 \end{bmatrix} \begin{bmatrix} SPEI\_DROUGHT \\ FAO \\ CPI\_KAZ \\ CPI\_RUS \\ ADM\_PRICES \\ GRAIN\_CROPS \\ IMP \\ EXP \\ \text{NER} \\ M2 \\ GDP\_gap \\ CPI/Food\_CPI \end{bmatrix}$$

$$B\eta_t = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & NA & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & NA & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & NA & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & NA & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & NA & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & NA & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & NA & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & NA & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & NA & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & NA & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & NA \end{bmatrix} \begin{bmatrix} SPEI_{DROUGHT} \\ FAO \\ CPI_{KAZ} \\ CPI_{RUS} \\ ADM_{prices} \\ GRAIN_{CROPS} \\ IMP \\ EXP \\ \text{NER} \\ M2 \\ GDP_{gap} \\ CPI/Food\_CPI \end{bmatrix}$$ [15]

[15] The -1 means giving negative shocks to SPEI variables, leading to drought condition.
NA entries are free parameters.
Diagonal = 1 (normalized) in *A* matrix

5. Results and Discussion: Impact of Drought on Inflation and Related Variables in Kyrgyzstan

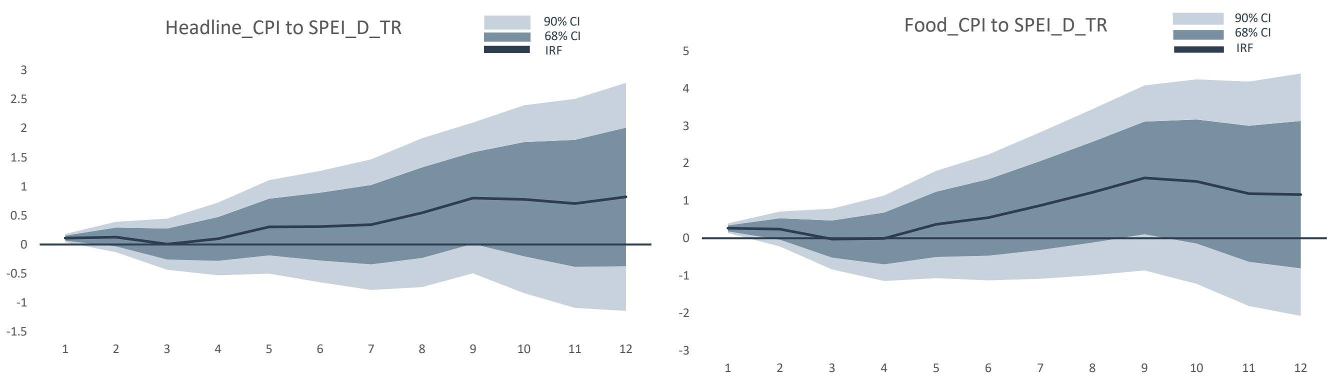
5.1. Impulse Responses of CPI and Food_CPI

The SVARX results, based on an over-identified recursive specification, indicate that negative drought shocks affect inflation dynamics in Kyrgyzstan, with distinct timing and magnitude for headline CPI and Food_CPI. The accumulated impulse response functions (IRFs) are calculated based on a one-standard-deviation structural shock (equivalent to 0.59 SPEI units). Unless otherwise noted, the text refers to 90% confidence intervals (CIs), while the corresponding figures display both 68% and 90% CIs.

The monthly-accumulated IRFs (Figure 5) show that a one-standard-deviation negative SPEI shock (hereafter referred to as a "drought shock") increases headline CPI by 0.07–0.13 p.p. within the first two months. This is followed by a delayed effect in the 9th month, where headline CPI rises by 0.8 p.p. (significant at the 68% CI). In comparison, the cumulative response of Food CPI is pronounced: it rises by 0.3 p.p. in the first two months, reaches 1.3 p.p. by month 8, and peaks at 1.7 p.p. in the 9th month. However, it should be noted that for both indices, the inflationary impact in the 9th month is only statistically significant at the 68% CI.

Overall, the impulse responses show that drought shocks exert a substantially stronger effect on Food_CPI than on headline CPI, with magnitudes roughly twice as large. This pattern reflects the greater sensitivity of food prices to drought variability. The findings are consistent with the structure of the CPI basket in Kyrgyzstan, where food accounts for around 46% of headline CPI, implying that food prices serve as a key transmission channel from drought conditions to overall inflation.

Figure 5. Accumulated Response to Structural VAR Innovations 68-90% CI using analytic asymptotic S.E.s



In addition, the IRFs demonstrate that negative SPEI drought shocks affect several other variables that transmit drought conditions to headline and food CPI (see Figure 6). Grain production is the most immediately affected, exhibiting a sharp and statistically significant decline within the first five months, with a peak cumulative reduction of 10 p.p. in months 5-6. This confirms that drought conditions directly reduce crop yields, consistent with the country's reliance on rain-fed agriculture.

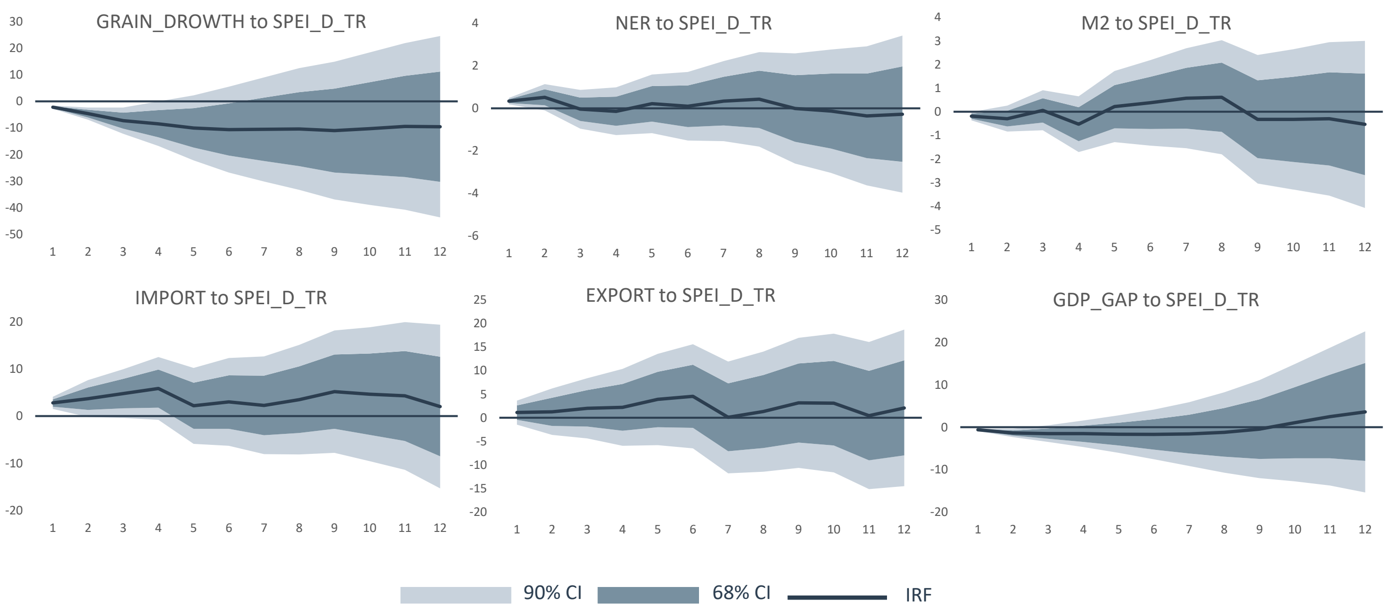
Drought-induced declines in grain production trigger sequential adjustments in trade flows. Imports increase by 2.8–5.9 p.p. in the first four months, reflecting efforts to compensate for domestic shortages.

However, exports appear less directly tied to the drought shock. As a result, drought-induced supply disruptions primarily affect the economy via reduced domestic supply and higher import dependence, rather than through a contraction in exports. This indicates that Kyrgyzstan's trade system responds quickly to agricultural shocks and further highlights the country's reliance on imports.

The nominal exchange rate (NER) also responds statistically significantly to drought shocks. It depreciates by 0.3–0.5 p.p. in the first two months before dissipating. These movements likely reflect the transmission of drought-induced trade imbalances: reduced grain output raises imports, causing pressure on the domestic currency. Taken together, the co-movement of higher imports and depreciation after drought shocks suggests that increased imports contribute to exchange-rate pressure, which in turn amplifies pass-through to CPI and Food_CPI.

In addition, M2 falls in the first two months by approximately 0.2–0.3 p.p. in response to the drought shock. A plausible interpretation is a policy reaction function: depreciation pressures prompt the NBKR to tighten liquidity, contracting the money aggregate to stabilize the exchange rate and contain inflation. This, however, comes with real-side costs. The output gap deteriorates by about 0.6 to 1.3 p.p. over the first three months, with effects statistically significant at both the 68% and 90% CIs. The sequence is lower agricultural output, higher imports, currency depreciation, and tighter liquidity, resulting in a near-term contraction in economic activity alongside rising inflation.

Figure 6. Accumulated Response to Structural VAR Innovations 68-90% CI using analytic asymptotic S.E.s



5.2. Reinforcing Transmission Channels: Responses to Other Key Shocks

Considering the significance of several variables with respect to SPEI drought, this section also examines the responses of headline and food CPI to other key shocks. These additional responses serve as complementary evidence supporting the transmission mechanisms identified in previous subsection. Across all shocks, the responses of headline CPI and Food_CPI are broadly similar in direction, with the main differences occurring in their magnitudes.

Starting with shocks to GRAIN_CROP, the responses do not affect headline CPI or Food_CPI, although drought shocks do reduce yields of grain crops. A possible explanation is the offset/mitigation effect of trade flows, which play an important role during periods of agricultural shortage. Indeed, structural shocks to imports and exports influence domestic supply conditions and thereby affect price levels. A positive import shock increases headline CPI by 0.2–0.3 p.p. and Food_CPI by 0.3–0.4 p.p. during the first three months, while export shocks do not significantly affect either headline or food CPI. These findings align with the trade-adjustment channel described earlier, showing how trade flows interact with production shocks to amplify or mitigate inflationary pressures. For example, an increase in imports substitutes for the tightened domestic supply, which raises prices.

Shocks to the nominal exchange rate (NER) exhibit a clear positive relationship with both CPI measures. Specifically, a local currency depreciation raises headline CPI by approximately 0.3 p.p., peaking in the fourth month. This effect even more pronounced for food prices, which increase by 0.4 percentage points in month 4 and reach 0.63 p.p. by the 9th month. While the impact on food prices appears more persistent than on headline inflation, this extended duration is statistically significant only at the 68% CI. This result is consistent with the notion that appreciations ease imported price pressures, whereas depreciations intensify them, especially for food products with high import content.

The response of headline CPI to a positive output gap shock is positive and statistically significant at the 90% CI, while for Food_CPI it is not statistically significant at that CI. This insignificant response of Food_CPI suggests that output shocks play a limited role in driving food price dynamics, in contrast to headline inflation, which reflects broader demand-side pressures (because of services and non-tradables).

In addition, structural shocks to strictly exogenous variables also have statistically significant effects on both CPI measures. Positive shocks to the FAO Food Price Index raise both CPI measures, with stronger and faster pass-through to Food_CPI (0.1–1.4 p.p. from months 1 to 4) and a headline CPI increase of about 0.4 p.p. by month 3 at the 90% CI. Kazakhstan’s CPI also transmits to domestic prices: a one-standard-deviation increase raises headline and Food_CPI by up to 1.0 and 1.6 p.p., respectively, with effects persisting for roughly six months for headline CPI and four months for Food_CPI. Russia’s CPI has a positive and statistically significant impact in the first month – about 0.2 p.p. for headline CPI and 0.3 p.p. for Food_CPI at the 90% CI. A positive shock to administered prices increases headline CPI by around 0.2 p.p. in the first month and then fades, with no statistically significant effect on Food_CPI. Figure 8 illustrates these dynamics, indicating that alongside domestic drought conditions, global markets and regional price developments also transmit to domestic inflation through the FAO index and the CPIs of Kazakhstan and Russia.

Overall, these responses reinforce the mechanisms identified in the previous subsection. Domestic production conditions, trade adjustments, global food price developments, and exchange-rate movements interact to shape inflation outcomes in Kyrgyzstan. While the responses of headline and food CPI often move in the same direction, differences in magnitude highlight the central role of food prices as the primary channel through which shocks, whether domestic or external, transmit to overall inflation. The observed cases where headline CPI increases despite an increase in the output gap, or differences in the periods of persistence in the reaction of both measures, further emphasize the heightened sensitivity of food prices to sector-specific and external factors.

Figure 7. Accumulated Response to Structural VAR Innovations 68-90% CI using analytic asymptotic S.E.s

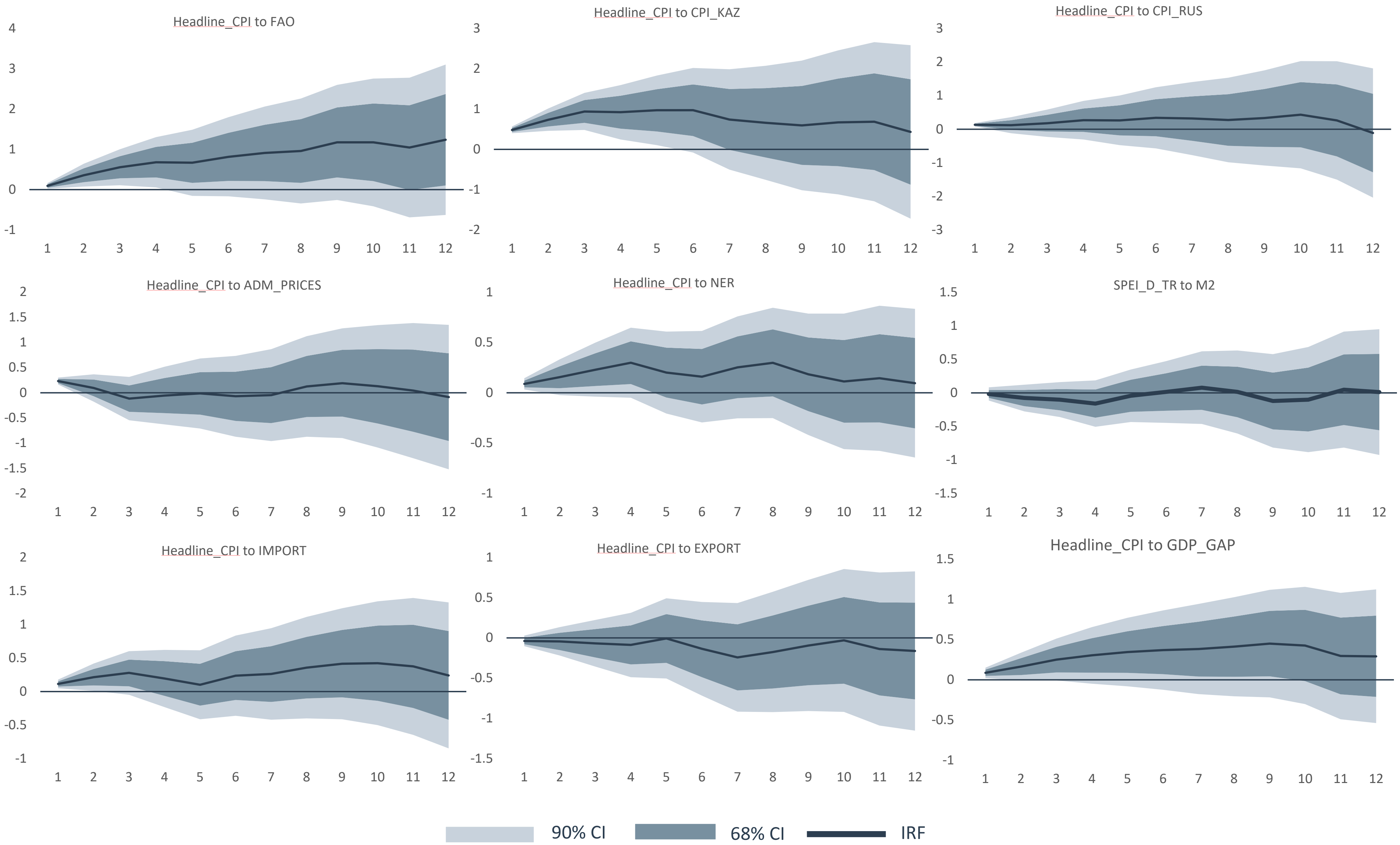
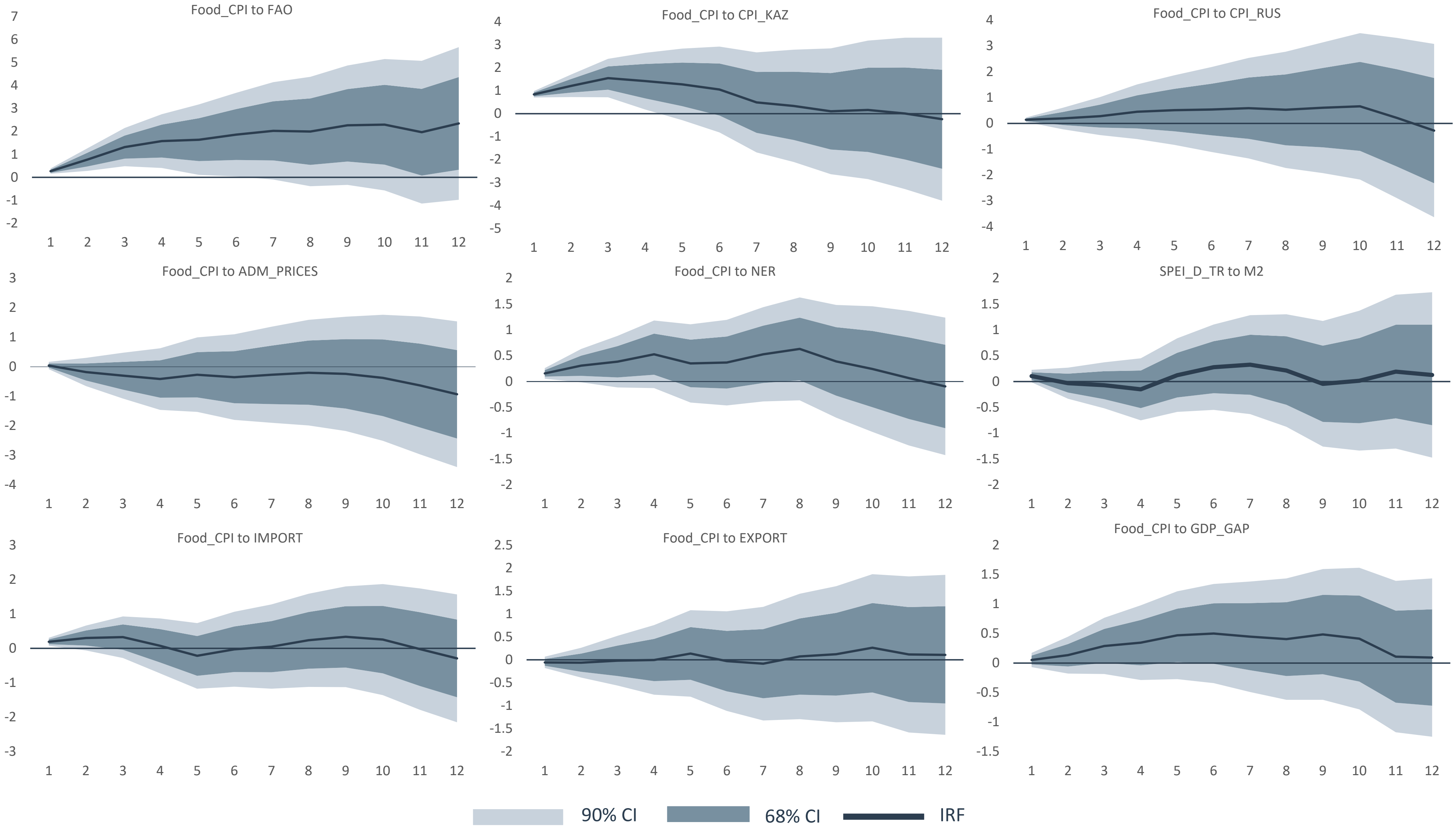


Figure 8. Accumulated Response to Structural VAR Innovations 68-90% CI using analytic asymptotic S.E.s



6. Conclusion

This paper empirically studied the impact of drought conditions measured by the SPEI on headline and food CPI, considering the agriculture sector as the transmission channel. It utilized monthly data from 2000 to 2022 on the SPEI as a proxy for climate variability, along with a number of macroeconomic variables selected based on economic theory, empirical findings, and institutional knowledge. The study employed IRFs from SVARX models.

The results confirm the central hypothesis that drought shocks exert statistically significant and inflationary effects on both headline CPI and food CPI. The magnitude of the response is notably larger for food prices, consistent with the structure of Kyrgyzstan's CPI basket, where food accounts for approximately 46 percent of headline inflation. A one-standard-deviation drought shock raises headline CPI cumulatively by about 0.07–0.13 p.p. in the first two months, reaching roughly 0.8 p.p. by the ninth month. In contrast, food CPI increases by about 0.3 p.p. in the short run and by up to 1.7 p.p. over the same horizon, highlighting the heightened sensitivity of food prices to climate-related disruptions.

The analysis indicates that the inflationary impact of drought operates through indirect but economically meaningful channels. Drought shocks significantly reduce grain production, by around 10 p.p., reflecting Kyrgyzstan's dependence on rain-fed agriculture. While these production losses do not translate into an immediate direct effect on consumer prices, they spill over into trade flows and macroeconomic conditions. Imports increase by approximately 2.8–5.9 p.p. following a drought shock, contributing to exchange-rate depreciation of about 0.3–0.5 p.p. in the first two months. This depreciation, in turn, amplifies inflationary pressures through higher import prices.

At the same time, the monetary response appears contractionary. Money supply declines by 0.2–0.3 p.p., possibly reflecting liquidity tightening by the National Bank of the Kyrgyz Republic aimed at stabilizing the exchange rate and containing inflation. While this response helps mitigate inflationary pressures, it also contributes to a contraction in economic activity, with the output gap declining by 0.6–1.3 p.p. during the first three months following the drought shock. Together, these dynamics trace a coherent transmission mechanism linking climatic shocks to inflation through production losses, trade adjustments, exchange-rate movements, and monetary conditions.

Beyond domestic channels, the results also highlight the importance of external factors. Global food prices, captured by the FAO index, as well as inflation developments in Kazakhstan and Russia, independently contribute to domestic inflation dynamics. This underscores Kyrgyzstan's dual exposure to climate-related domestic shocks and external price pressures transmitted through trade and regional integration.

From a policy perspective, the findings emphasize the need to strengthen food supply resilience, improve the flexibility and capacity of trade to absorb agricultural shocks, and closely monitor exchange-rate dynamics in the face of climate-related disturbances. Integrating climate indicators such as the SPEI into inflation forecasting and policy frameworks could enhance the accuracy and timeliness of monetary policy responses.

Finally, the study points to avenues for further research, particularly through the use of regional SPEI indicators, which can capture additional insights into interaction with global food markets and enhance approaches for forecasting and analyzing international price changes.

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