Rice price inflation dynamics in the Philippines

Antonio, Ronald Jeremy and Valera, Harold Glenn and Mishra, Ashok and Pede, Valerien and Yamano, Takashi and Vieira, Bernardo Oliva

International Rice Research Institute, Laguna, Philippines, Bangko Sentral ng Pilipinas, Metro Manila, Philippines, Arizona State University, Arizona, USA, Asian Development Bank, Metro Manila, Philippines, Lund University, Lund, Sweden

30 April 2024

Rice price inflation dynamics in the Philippines

Ronald Jeremy Antonio[1], Harold Glenn Valera[1,2], Ashok K. Mishra[3], Valerien Pede[*1], Takashi Yamano[4], Bernardo Oliva Vieira[1,5]

[1*] International Rice Research Institute, Laguna, Philippines
[2] Bangko Sentral ng Pilipinas, Metro Manila, Philippines
[3] Arizona State University, Arizona, USA
[4] Asian Development Bank, Metro Manila, Philippines
[5] Lund University, Lund, Sweden

Email: v.pede@irri.org *(Corresponding author)*

Abstract

In recent years, prices fertilizer, cereals and rice prices have increased significantly due to the Russia-Ukraine war and the export restrictions imposed by India. Thus resulting in higher rice prices in the Philippines. This paper examines the dynamic relationship between rice price inflation and key drivers in the Philippines by estimating a panel vector auto-regression model using monthly data from 1994 to 2023. We find evidence that the effect of world rice price shock is generally the larger and more persistent than the effects of other factors. We also find that movements in rice price inflation are explained by domestic fuel price shocks and to a lesser extent by the world urea price shocks. The impulse response functions driven by those three shocks vary over the sample, especially before a change in food policy such as the imposition of the rice tariffication in 2019. Further analysis suggests that El Niño Southern Oscillation shocks tend to induce an inflationary effect on rice prices in high-poverty and rice-sufficient regions. Our results have important food policy implications for rice markets, and offer timely insights into the desirability of current proposals to reduce rice prices for consumers and improve existing support for famers to boost rice production.

Keywords: Panel data, consumer price index, input prices, weather, fuel price persistence shocks, commodities

JEL Classification: C23; E31; N35; Q18

1. Introduction

In recent years, because of the Russia-Ukraine war and export restrictions imposed by India, fertilizer prices, cereal prices, and global rice prices have increased significantly. Rising food prices have received significant attention because of the growing priority in addressing the problem of food insecurity. Rising food prices are exacerbated in developing countries, where much of the price strongly contributes to household budgets and economic activity. Furthermore, staple food crops such as rice and wheat dominate food budgets in many developing countries, whose food consumption accounts for much of household income. In this case, Wu and Xu (2021) posited that overall inflation follows the same trend when food prices increase. Thus, consumer welfare decreases significantly. With higher food prices inducing welfare losses by increasing poverty incidence and worsening health outcomes, the current literature has been geared toward determining what drives food price inflation. The emerging results link food prices to domestic production (Shively and Thapa, 2017; Durevall et al., 2013); prices of fuel and other related commodities (Termos et al., 2013; Shively and Thapa, 2017); international market factors such as world prices, transportation costs, and exchange rates (Shively and Thapa, 2017; Iddrisu and Alagidede, 2020; Durevall et al., 2013); and climate events (Ubilava, 2017; Ubilava and Abdolrahimi, 2019). The results provide significant information on the factors affecting prices, but few studies focus on specific food commodities such as rice.

Therefore, our study aims to estimate the dynamic relationship between rice price inflation and the drivers of this inflation in the Philippines. The study uses regional monthly panel data from January 1994 to March 2023 and a panel vector auto-regression (PVAR) modeling approach. The PVAR approach uses a sufficiently large sample size to detect associations between rice price inflation and its possible drivers: world price of rice, fuel price inflation, world urea price, and El Niño Southern Oscillation (ENSO). The PVAR methodology helps determine the magnitude and persistence of shocks related to rice price inflation. Indeed, panel data should be used since the regional inflation differences might reflect differences in price adjustments between regions (Valera et al., 2022). PVAR is advantageous since it allows multiple variables to be treated as endogenous (Liaqat, 2019), thus allowing the likely endogenous interaction of world rice and urea prices, rice price inflation, and fuel price inflation.

Our study contributes to the empirical literature in several ways. First, the study investigates a specific commodity, rice. It puts it in the context of the Philippines, where rice is not only a staple food crop but also a prioritized crop in public policy and government support. Second, the study is timely in the current landscape, given the looming threats such as climate events (e.g., El Niño), current trade restrictions, and price movements caused by the Russian invasion of Ukraine, which might destabilize Filipino rice prices. Third, the study uses the panel VAR approach that Love and Zicchino (2006) introduced. The study also uses PVAR to efficiently estimate the magnitude and persistence of shocks related to rice price inflation. This approach also captures the unobserved factors among the cross-sections of data, such as the economic differences between the regions of the Philippines. To the best of our knowledge, the only studies in the current literature on food inflation that use any specification of VAR are Hammoudeh et al. (2015) and Bhattacharya and Jain (2020). Those studies investigated the impacts of restrictive monetary policies on different measures of inflation, and Valera et al. (2022) studied the effects of rice prices on overall inflation.

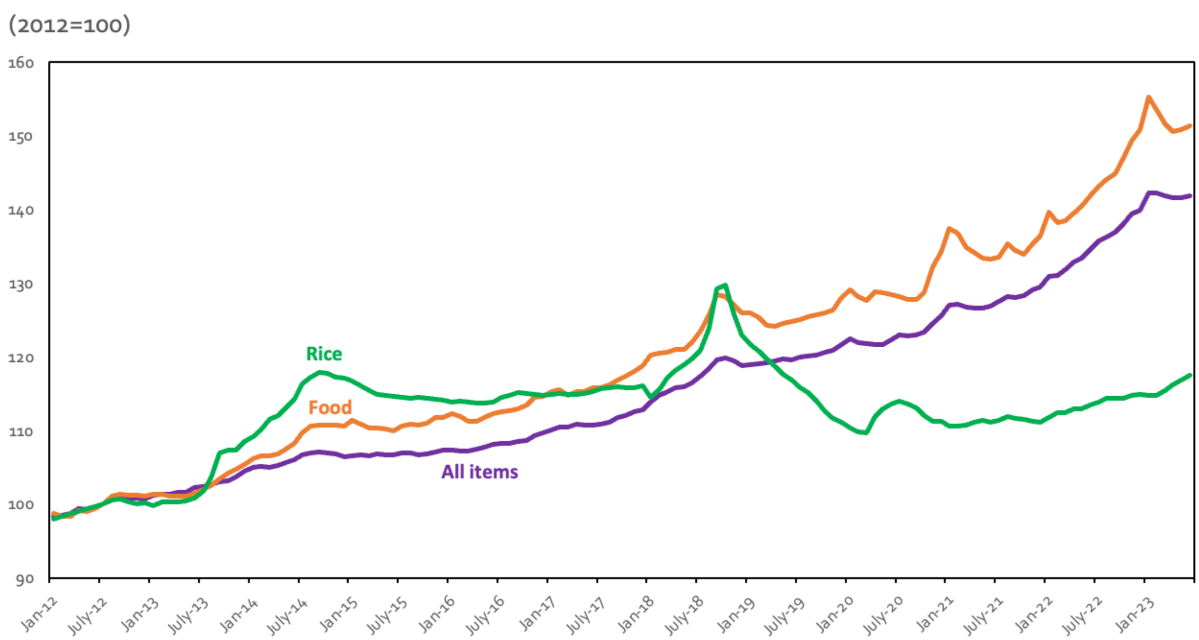
The findings show a larger and more persistent inflationary effect on world rice prices compared to other determinants. All drivers mentioned also exhibited inflationary effects, albeit in different magnitude and length of impact. The robustness checks also show that rice production and supply are significant determinants in identifying what drives rice price inflation in each region.

The rest of this study is organized as follows. Section 2 briefly overviews the rice price situation in the Philippines and Section 3 presents relevant existing literature. Section 4 discusses the methodology and data. Section 5 describes the data used in the study. Section 6 presents the results and Section 7 concludes the study.

2. Rice Price Situation in the Philippines

The Philippines has consistently ranked among the top domestic rice consumers and was sixth in 2022, accounting for approximately 16 million metric tons of consumption (USDA, 2023). With most Filipino households being net rice consumers, rice prices have historically been higher than the country's overall inflation (Figure 1). This aligns with the earlier observation that food expenditure dominates households' budgets in most developing countries and strongly influences the overall consumer price index (CPI). This is also evident even for rice alone since studies have found that the majority of the poor households in the country spend more than 20% of their total budget on rice (Balié and Valera, 2020), and rice price inflation is a major driver of the country's overall CPI (Valera et al., 2022).

Figure 1. Inflation dynamics in the Philippines, 2012–2023.

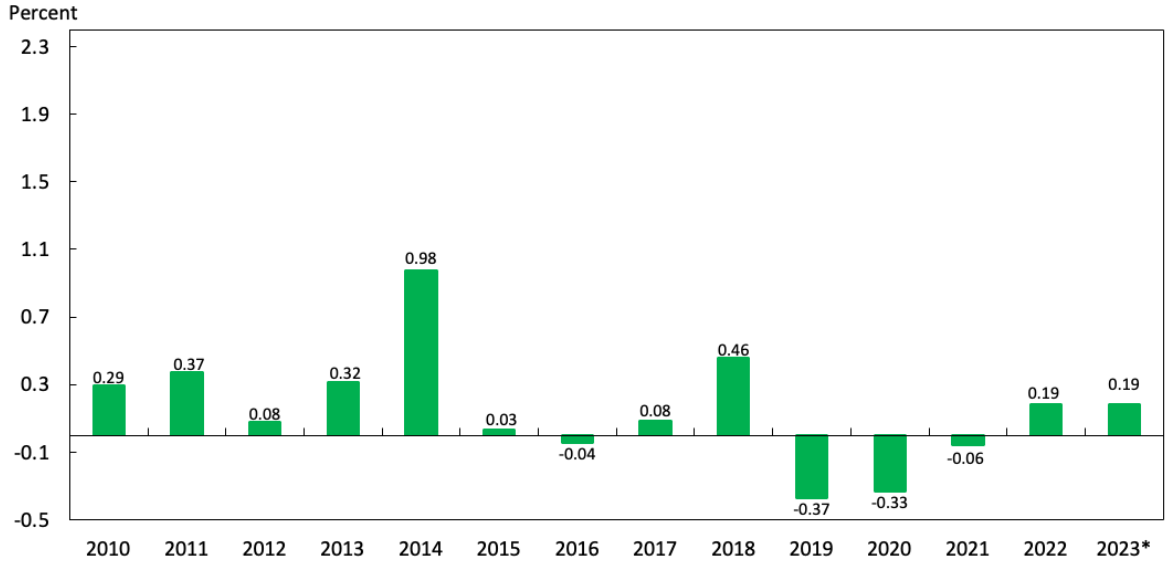


Source: Philippine Statistics Authority

Historically, there have been strong upward trends in the Philippines' domestic rice prices in 2007–2008, 2013–2014, and again in 2018, which have led to concern about increased food insecurity and poverty across the country. Higher food prices limit access to affordable food for people experiencing poverty. The rising prices were one of the main motivations for the Philippine government passing the Rice Tariffication Law (RTL) in March 2019. In essence, the law removes the protectionary quantitative restrictions placed on rice imports and replaces them with tariffs in compliance with those of the World Trade Organization (WTO). The National Economic and Development Authority (2022), the country's socioeconomic planning body, proclaimed that the RTL is the best model that the country has to help both consumers and producers in the Philippines. Theoretically, removing the quantity restrictions on rice imports should decrease consumer retail prices. Then, the government can use the tariff revenues to assist the rice farmers formerly protected through quantity restrictions. The law further mentions that, before 2019, rice was the biggest contributor to inflation, but, since the passage of the law, rice prices have had a minimal contribution. In line with the statements above, rice price inflation has been much less than general overall inflation and food price inflation following the implementation of the RTL in March 2019, as seen in Figure 1.

However, rice price inflation in the Philippines has risen since 2022, contributing 0.19% to headline inflation (Figure 2). Local experts have concluded that this might be due to diminished production. The decline in output might also be due to other factors such as low fertilizer application caused by high fertilizer prices (resulting from Russia's invasion of Ukraine), low farmer motivation due to the low farm-gate prices farmers receive, the decrease in area planted due to land conversion, and unfavorable weather conditions (Business World, 2022). In a recent study, Valera et al. (2022) found that rice price is a major contributor to overall inflation in the Philippines, even having a larger impact than fuel prices.

Figure 2. Contribution of rice inflation to annual year-on-year inflation, Philippines, 2010–2023.



Source: Authors' computation based on inflation data from the Philippine Statistics Authority

Additionally, since 2022, significant world events have caused disruptions in global food security and prices. Record highs in fertilizer prices were triggered by Russia's invasion of Ukraine (Hebebrand and Glauber, 2023), followed by significant increases in cereal prices, particularly for wheat, because of the collapse of the Black Sea Grain Initiative (Poursina et al., 2023; Mottaleb et al., 2022; Lin et al., 2023), followed by India's export ban on non-basmati rice (Shan, 2023). With agricultural input and cereal prices increasing significantly in the world market, the Philippines is vulnerable to price disruptions because of its reliance on imports to meet domestic consumption demand. With the current market situation, especially in the Philippines, prices are markedly affected by the global market. Indeed, this research is timely and explores what drives rice price inflation in the country.

3. Literature Review

Previous studies have discussed the drivers of overall inflation and inflation for specific food commodities or food groups in national and global contexts in great detail; however, few studies have specifically focused on rice price inflation. Some studies have looked into the contribution of food inflation to overall inflation. In a recent study, Valera et al. (2022) used panel VAR and data from the Philippines, a top rice-consuming country, and found that rice price shocks have a more significant and prevailing impact than fuel price and remittance shocks. Tule et al. (2019) explored several agricultural commodities and found that Nigeria's top 12 agricultural commodities contribute to most headline and food inflation. Using error correction models, Zhang et al. (2014) showed that average food prices contribute to a significant portion of China's consumer price index. Looking into a more disaggregated food group, the authors found that major cereals such as wheat, maize, sorghum, and barley are the major drivers of inflation among the food groups. Considering that China is a major importer of cereals, the authors concluded that international food prices and exchange rates are also major drivers of food inflation in the country.

The existing literature also contains studies investigating the factors affecting inflation in a group of countries. For example, Nguyen et al. (2017) examined the impact of supply and demand shocks on inflation in sub-Saharan Africa. Contrary to the initial perception in the region, supply shocks such as world prices of various commodities, weather shocks, and inflation spillovers from other countries account for 45% of the inflation in the region. In comparison, the remaining 55% of the inflation is caused by demand shocks, the majority of which are accounted for by changes in exchange rates and shocks in the output gap. Similalry, Termos et al. (2013) examined the factors affecting inflation in the Gulf Cooperation Council (GCC) countries. As expected for Middle Eastern countries, changes in crude oil prices are a major factor in determining inflation. Given that the GCC countries are net senders of remittances—essentially money leakages out of their economies—these were thus deflationary.

Exploring studies that examine the factors affecting food prices, Shively and Thapa (2017) hypothesized that transportation infrastructure was critical in rice and wheat prices in a developing country such as Nepal. Their study found that the quantity and quality of transportation infrastructure significantly lowered local commodity prices. Related to this, central market and border prices also drove local prices, showing price cointegration between local markets. Production is negatively correlated with local prices for rice, showing that much of what drives rice prices is within the domestic market. Conversely, the study of Iddrisu and Alagidede (2020) investigated the factors affecting food inflation in South Africa. Using the quantile regression procedure, the results showed that factors positively correlated with rice price inflation are the country's exchange rate, transportation costs, and the world food price index. Additionally, monetary policy is positively correlated. Although production is insignificant, many of the price drivers in South Africa are from the international market.

Aside from the study of Iddrisu and Alagidede (2020), other studies on food price inflation also investigated the possible impacts of monetary policy—expected to curb inflationary pressure. For instance, Durevall et al. (2013) studied the inflation dynamics in Ethiopia. Grouping commodities into cereal, food, and non-food commodities, the authors reported that money supply growth affected non-food prices only in the short run. The study further noted that movements in international prices and domestic production are the primary sources of price movement, which is to be expected for developing countries. Bhattacharya and Jain (2020) examined the effectiveness of monetary policy in stabilizing food inflation between advanced and emerging economies. Similar to the findings of Iddrisu and Alagidede (2020), both advanced and emerging economies show that contractionary monetary policy only further increases and destabilizes food price inflation.

The impact of El Niño Southern Oscillation (ENSO) on cereal prices and yields has also been studied in recent years. For example, Ubilava (2017) examined the effect of positive El Niño and negative La Niña ENSO shocks on wheat prices using the vector smooth transition auto-regressive modeling framework. The results showed that storage dynamics of wheat prices generally trended downward during El Niño shocks and upward during La Niña shocks. The author noted that the price responses to La Niña are higher than during El Niño. Further, Ubilava and Abdolrahimi (2019) examined the impact of ENSO on maize yield in lower-income teleconnected countries. In the case of maize yield, it decreases under El Niño and La Niña occurrences. Further, the authors found that, although maize is predominantly produced in higher-income countries, the total yield reduction is more pronounced and the per-country reduction is much higher in low-income and low-teleconnected countries where access to information is much lower.

The existing literature suggests that food prices contribute significantly to overall inflation. Several factors that might affect food price inflation have also been identified. These factors range from domestic ones, such as local prices (e.g., regional, central market prices), price of substitute commodities, transportation infrastructure, fuel price, and domestic production, to global ones, such as transportation costs, world prices, and exchange rates. Climate events have also been seen as a contributing factor to both the production and price of cereals. Meanwhile, expansionary and contractionary monetary policy seems to have little to no effect on food price inflation.

4. Econometric Framework

This study uses the panel VAR method developed by Love and Zicchino (2006). As stated by Liaqat (2019), the panel VAR approach is similar to other traditional VAR models. It treats all variables as endogenous, which is advantageous in our case given the likely endogeneity between domestic rice price inflation, world rice and urea prices, and fuel price inflation. The panel VAR method also benefits from a panel data framework that allows for unobserved individual heterogeneity across all variables by introducing fixed effects to the model (Shen et al., 2015). In terms of the variables used in our study, the world price of rice is considered a major driver of rice price inflation (*RPI*), given the Philippines' standing as one of the world's top rice importers. We use Thai 5% (*THAI*) broken rice prices to measure world rice prices. The drivers also include fuel price inflation (*FPI*) and world urea price (*UREA*) as measures of agricultural inputs, which affect agricultural productivity. Lastly, our study uses El Niño Southern Oscillation (*ENSO*) to measure climate events. The panel VAR model is estimated using the following equation:

$$X_{it} = A(L)X_{it-1} + f_i + \mu_i + \varepsilon_{it} \tag{1}$$

where X_{it} represents the five endogenous variables (*RPI, THAI, FPI, UREA, ENSO*), $A(L)$ is a matrix polynomial of a lag operator, and μ_i is a vector of region-specific effects. X_{it-1} is specified as the log-difference form of the endogenous variables. f_i denotes the fixed effects, while ε_{it} denotes the vector of residuals. When applying the panel VAR method, the assumption is that the error structure is similar across sections. Given that this assumption is likely to be violated allows for individual heterogeneity by introducing fixed effects f_i, denoted in Equation 1. However, since the assumption for fixed effects is that the individual effects would be correlated to their specific independent variables, using the traditional mean differencing approach to remove the fixed effects would likely lead to biased estimates (Shen et al., 2015). To avoid this problem, our study uses forward-mean differencing or orthogonal deviations (i.e., Helmert transformation) following Love and Zicchino (2006). The Helmert transformation ensures that heteroskedasticity and autocorrelation are absent in the model since each observation is weighted to standardized variance (Liaqat, 2019). In this procedure, the coefficients are estimated through the generalized method of moments using the lagged values of the regressors as instruments.

The error terms in Equation 1 are assumed to be independent. However, this is likely to be violated, given that weather and price shocks to the endogenous variables might still be correlated in practice. To estimate the shocks independently, decomposing the errors would be essential to make sure that the errors are orthogonal. To this end, we use the Cholesky decomposition of the variance-covariance matrix of residuals to isolate the response of inflation to orthogonalized impulses of the other variables in the vector X_{it}. The impulse-response functions (IRFs) are computed from the estimated panel VAR coefficients. Since the ordering of the variables matters in this procedure to generate the response of rice price inflation to its drivers, we arranged them in descending order based on their degree of exogeneity: ENSO, fuel price inflation, urea price, the world price of rice, and rice price inflation. The above serves as the baseline model specification. We also considered alternative orderings to ensure that the chosen system representation does not drive the results. The objective is to check whether or not the baseline results for the IRFs are robust to the different causal specifications. Robustness checks are also performed by estimating the baseline model specification of panel VAR (a) across sub-samples of regions based on their level of poverty incidence and (b) across sub-samples of regions based on their rice self-sufficiency levels. Lastly, an estimation of confidence intervals is required to analyze the impulse-response functions. Indeed, Shen et al. (2015) suggested using Monte Carlo simulations to generate confidence intervals based on the estimated coefficients and the standard errors. The fifth and 95th percentiles of the distribution of the coefficients generated from 200 Monte Carlo simulations are used as the confidence interval for the impulse responses.

5. Data

We used a balanced dataset for the 17 regions in the Philippines from 1994M1 to 2023M3. Monthly data on rice and fuel prices came from the Philippine Statistics Authority. Monthly data on the world price of rice based on Thai 5% broken rice and world urea prices were based on the monthly data published on the World Bank Commodity Price Data or Pink Sheet. The exchange rate data came from the Central Bank of the Philippines, while the CPI data came from the Philippine Statistics Authority. This study used a monthly series of indices depicting ENSO cycles using sea surface temperature (SST)–based measures in the equatorial Pacific region. The SST-based measure depicts deviations from the average historical temperatures in a given month over the centered 30-year base periods. The National Oceanic and Atmospheric Administration tabulates it. Thai 5% broken rice and urea prices are presented in real terms and in Philippine peso terms by converting to the local currency through average monthly exchange rates and deflating with national-level average monthly CPI.

Because of the nature of the data for world rice price, urea price, and ENSO, only the rice and fuel price inflation variables have regional variations. Table 1 presents the summary statistics for the two variables. From the table, it is noticeable that fuel price inflation is generally higher and more volatile than rice price inflation. The regions with the highest average rice price inflation are the National Capital Region (NCR), Cordillera Administrative Region (CAR), and Central Visayas, whose mean rice consumer price index is above 70. It is important to highlight that these three regions are among the lowest in terms of rice production in the country. Meanwhile, fuel price inflation is highest in Eastern Visayas, Zamboanga Peninsula, Northern Mindanao, and SOCCSKSARGEN, among the country's poorest regions.

Table 1. Descriptive statistics for inflation variables, Philippines, 1994–2023.

Region	Rice price inflation (RPI)		Fuel price inflation (FPI)	
	Mean	Standard deviation	Mean	Standard deviation
NCR	70.151	22.858	71.873	32.837
CAR	72.292	19.103	67.926	34.329
Ilocos Region	68.450	22.172	71.135	34.547

Cagayan Valley	66.884	22.898	72.076	33.356
Central Luzon	67.763	23.568	69.354	34.283
CALABARZON	67.744	23.340	68.695	32.998
MIMAROPA	67.188	23.050	68.705	35.421
Bicol Region	67.246	22.596	71.333	34.599
Western Visayas	69.395	20.773	67.825	33.159
Central Visayas	73.056	17.955	69.005	33.843
Eastern Visayas	65.295	24.243	76.451	37.780
Zamboanga Peninsula	68.975	20.335	74.063	35.792
Northern Mindanao	68.714	23.112	76.729	33.162
Davao Region	67.168	22.430	72.667	35.216
SOCCSKSARGEN	66.131	21.491	77.271	35.717
Caraga Region	66.308	21.464	69.904	35.325
BARMM	63.529	24.443	72.059	34.316

Note: NCR is the National Capital Region. CAR is the Cordillera Administrative Region. BARMM is the Bangsamoro Autonomous Region in Muslim Mindanao. CALABARZON is an acronym for the region comprising five provinces: Cavite, Laguna, Batangas, Rizal, and Quezon. MIMAROPA is an acronym for the region comprising Mindoro, Marinduque, Romblon, and Palawan. ARMM refers to the Autonomous Region of Muslim Mindanao. SOCCSKSARGEN is an acronym for the region that includes four provinces (South Cotabato, Cotabato, Sultan Kudarat, and Sarangani) and one city (General Santos).
Source: Authors' computation based on inflation data from the Philippine Statistics Authority

Tables 2a and 2b present our tests for the non-stationarity of each variable. The conventional DF-GLS test was used to check for the stationarity of each variable with and without a trend. Table 2a presents the non-stationarity results for variables with regional variation: rice and fuel price inflation. Rice price inflation with a trend is stationary at 10% only for CALABARZON and Eastern Visayas in the DF-GLS test. In comparison, fuel price inflation is stationary only for Cagayan Valley and Western Visayas at 5% and for Ilocos Region at 10%. On the other hand, Table 2b shows the unit root test results for world rice price, world urea price, and climate event (ENSO), with the variables not having regional variations. The table reveals stationarity for urea prices in the tests without a trend and for ENSO for the tests with a trend. Given that there are only a few stationary series and none are stationary at the 1% level, the current analysis uses the data in the first-differenced natural logarithm form.

Table 2a. Unit root tests for stationarity among variables with regional variation, Philippines, 1994–2023.

Region	DF-GLS test (no trend)		DF-GLS test (with trend)	
	RPI	FPI	RPI	FPI
National Capital Region	0.851	-0.419	-2.355	-2.310
Cordillera Administrative Region	1.034	0.592	-1.327	-2.392
Ilocos Region	1.465	0.210	-2.594	-2.719*
Cagayan Valley	1.168	-0.057	-1.947	-3.010**
Central Luzon	1.465	0.376	-1.981	-3.043
CALABARZON	1.970*	0.063	-1.453	-2.924
MIMAROPA	1.151	0.539	-2.639	-1.713
Bicol Region	1.413	0.246	-1.688	-2.008
Western Visayas	1.062	0.105	-1.894	-3.185**
Central Visayas	0.888	0.116	-1.701	-2.068
Eastern Visayas	1.739*	-0.084	-1.758	-2.606
Zamboanga Peninsula	0.321	0.126	-2.026	-1.970
Northern Mindanao	1.348	0.053	-1.021	-2.552
Davao Region	0.685	0.723	-1.693	-2.527
SOCCSKSARGEN	1.111	0.042	-1.030	-2.602
Caraga Region	1.027	0.230	-1.111	-2.380
BARMM	1.950*	0.123	-2.224	-2.251

*, ** indicate statistical significance at 10% and 5%, respectively. Optimal lag length selection is based on the Schwarz information criterion (SIC).

Table 2b. Unit root tests for stationarity among variables without regional variation.

Variable	DF-GLS test (no trend)	DF-GLS test (with trend)
THAI	-2.092	-2.963
UREA	-2.903*	-4.306
ENSO	-1.675	-5.768*

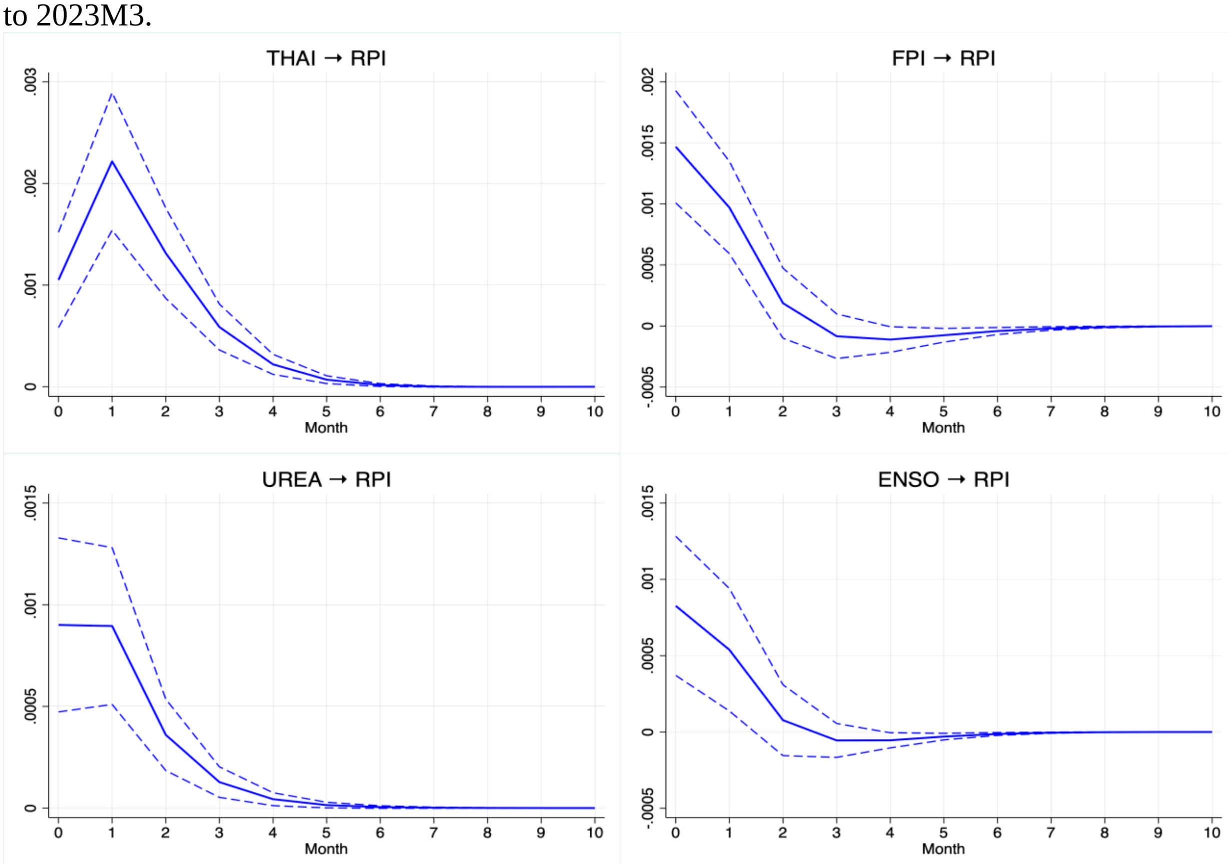
* indicates statistical significance at 10%. Optimal lag length selection is based on the Schwarz information criterion (SIC).

6. Results and Discussion

6.1 Baseline results

The panel VAR specified in Equation 1 is used to determine the impact and the magnitude of the factors affecting rice price inflation. Figure 3 depicts the impulse-response functions estimated via panel VAR. The estimates in Figure 3 show the response of rice price inflation with a unit shock in the growth of world rice price (top right), urea price (top left), fuel price inflation (bottom right), and climate event (ENSO) (bottom left) for a ten-month period. To ensure the validity of the results, we conducted Granger causality Wald tests and checked the stability condition of all estimates. A significant positive response of rice price inflation to a shock in the world rice price (Thai 5% price) peaks after one month and then dissipates over five months. Dawe and Kimura (2023) and Iddrisu and Alagidede (2020) have argued that domestic rice prices would reflect some parts of the movements of world prices in open trade countries. Given that the Philippines is one of the world's top rice importers, the country's openness to trade also makes it highly vulnerable to world price shocks.

Figure 3. Orthogonalized impulse-response functions were computed via panel VAR, 1994M11 to 2023M3.



Note: The 95% confidence intervals are based on 200 Monte Carlo simulations.

The initial response of rice price inflation to a fuel price shock is the highest among the determinants of rice price inflation (Figure 3). Increases in fuel prices are often associated with increased rice prices because fuel prices affect both input and transportation costs. Our findings show that, although the initial response is high, the impact dissipates completely after three months. This is in line with the findings of Shively and Thapa (2017), who found that, although increases in oil prices generally lead to commodity price increases, they do not lead to many price disruptions. The relatively low impact of oil price increases is linked to improved transportation infrastructure, whether domestic or international, which cushions oil price shocks on domestic rice prices (Shively and Thapa, 2017; Iddrisu and Alagidede, 2020). We also observe a significant positive response of rice price inflation to a shock in urea prices. The impact is highest at the onset of the first month and then drops over five months (Figure 3). Although the peak of the response is lower relative to the impacts of world rice price and fuel price inflation, the impact is still felt for five months, essentially one planting season. The inflationary effect is expected since fertilizer cost is a significant portion of all production costs, amounting to 20% to 30% (Chau and Ahamed, 2022).

A climatic shock (SST) represented by ENSO causes a significant and positive immediate effect on rice price inflation. The response, however, is relatively low and has the lowest initial impact on rice price inflation and for a fairly shorter period, dissipating after three months. Declines in rice yields can explain the short duration of rice price inflation. The decrease in rice yields is primarily due to lower harvested area rather than lower rice output (Cao et al., 2023). Data from the Philippines show that harvested rice area decreased (11.15%) more than the decrease in paddy production (10.91%) 24 months before the strongest occurrence of El Niño from June 1997 to June 1998. Similarly, during the last occurrence of El Niño (October 2018 to September 2019) in the Philippines, harvested area decreased more (3.40%) than the reduction in paddy output (3.25%) during the 24 months before the El Niño occurrence. In cases when rice yields are decreasing because of less productive land, this can be mitigated by increasing the productivity of the remaining farmland by using more quality and quantity of inputs per unit of farmland.

6.2 Robustness checks

To check the consistency of our results, we estimate Equation 1 across sub-samples of regions based on the level of poverty incidence following Valera et al. (2022), who argue that inflation has a larger welfare impact on the poor. The categorization of households is based on Balié et al. (2021) on the 2015 Family Income and Expenditure Survey of the Philippines. Table 3 summarizes the categorization and poverty incidence.

Table 3. Unit root tests for stationarity among variables with regional variation, Philippines, 1994–2023.

Region	Poverty incidence	Classification
National Capital Region	4.9	Low
Cordillera Administrative Region	26.5	Medium
Ilocos Region	22.6	Low
Cagayan Valley	30.5	Medium
Central Luzon	13.4	Low
CALABARZON	10.6	Low
MIMAROPA	35.1	High
Bicol Region	40.6	High
Western Visayas	27.5	Medium
Central Visayas	34.2	High
Eastern Visayas	48.8	High
Zamboanga Peninsula	48.9	High
Northern Mindanao	50.8	High
Davao Region	30.8	Medium
SOCCSKSARGEN	37.5	High
Caraga Region	47.0	High
BARMM	76.2	High

Source: Author's computation based on the 2015 Family Income and Expenditure Survey

Using the computed poverty incidence in Table 3, we split our sample into three groups: low-, medium-, and high-poverty regions. Once again, we find evidence that the identified factors have significant rice price inflationary effects in the three poverty groups (Figure 4). The high heel-shaped inflation responses of rice price inflation due to world rice prices align with our baseline results, in which the response peaks after one month and declines over five to six months (Figure 4). However, we observe variations in the dynamics of this response across poverty groups. Contrary to the initial assumption, the initial response and persistence are greater among low- and medium-poverty regions than in high-poverty areas. A plausible explanation is that high-poverty regions are rice-producing regions with relatively more net rice producers. Related to this, rice price inflation has a much larger response to an ENSO shock in high-poverty areas than in both the low- and medium-poverty regions and the baseline results. The impulse-response functions in the second column of Figure 4 show no significant change in the direction and extent of rice price inflation response to fuel price inflation between the baseline results and poverty groups. Lastly, the impulse-response functions in the third column present the response of rice price inflation due to urea price shocks, showing that the impact is less persistent in low-poverty regions than in their counterparts.

Another subsample analysis was conducted between rice supply deficit and surplus regions to validate the assumption that the difference between the impulse-response functions is driven by regional rice production and availability. We create a regional self-sufficiency indicator following Bordey et al. (2016). The self-sufficiency index is computed by dividing per-capita rice availability by per-capita rice food use. Per-capita rice availability is calculated by converting paddy production to its milled equivalent (65% as the milling recovery rate) and dividing it by the regional projected population. Per-capita rice used for food is computed by converting regional per-capita rice consumption data (90% of the total food consumption). To simplify, the resulting self-sufficiency index is categorized into only two instead of the five classifications used in the reference. The regions are classified as insufficient if the self-sufficiency index is less than 1.25

and as sufficient if the index is greater than or equal to 1.25. Data on paddy production and projected population are obtained from the Philippine Statistics Authority. At the same time, regional per-capita rice consumption is computed using the 2021 Family Income and Expenditure Survey of the Philippines. Table 4 summarizes the regional categorization.

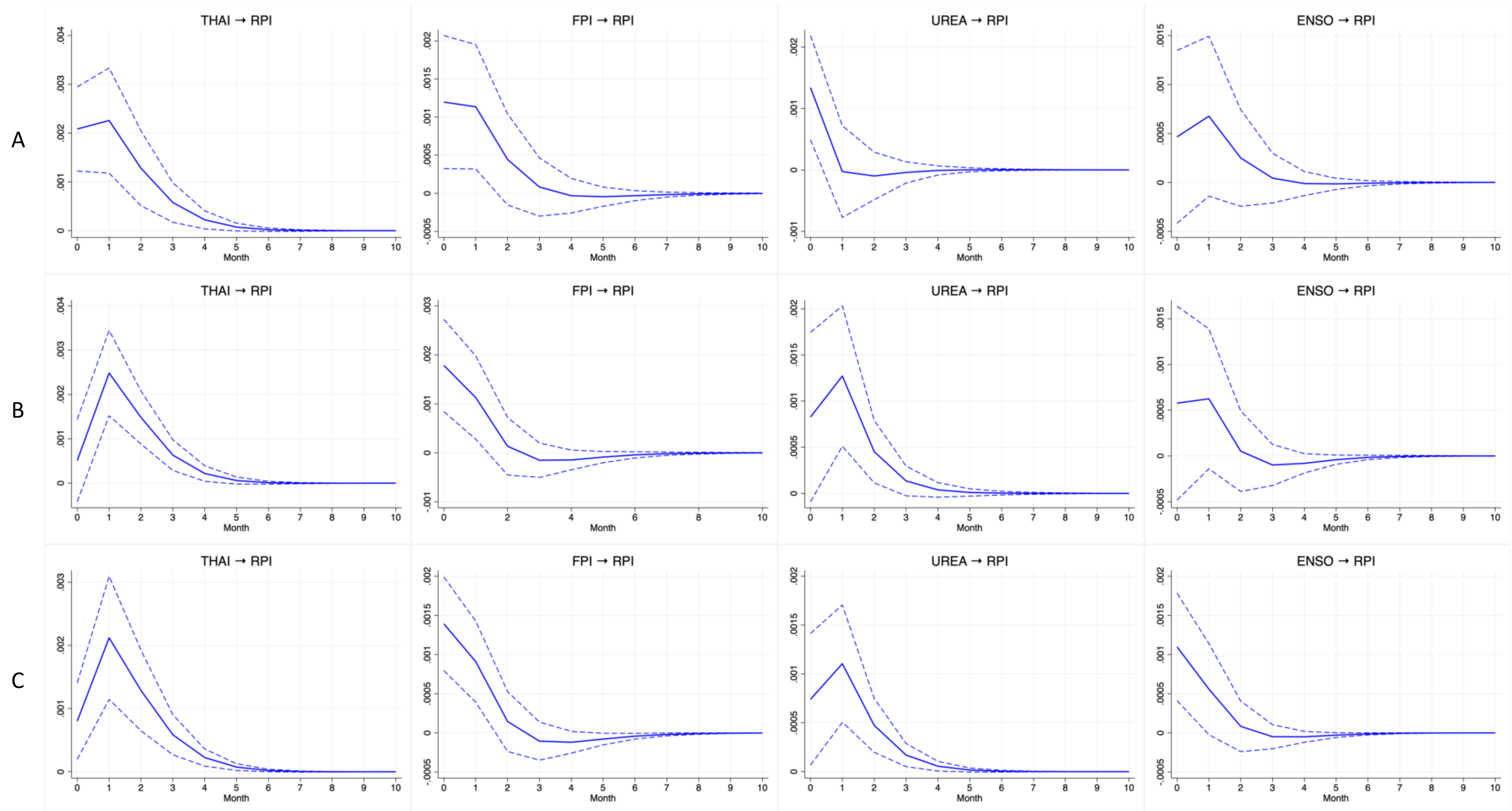


Figure 4. IRFs computed from estimated PVAR for (A) low-poverty, (B) middle-poverty, and (C) high-poverty incidence regions.

Table 4. Regional classification based on rice self-sufficiency, Philippines, 1994–2023.

Region	Rice availability	Rice food use	Self-sufficiency index	Classificati-on
National Capital Region	0.00	91.93	0.00	Insufficient
Cordillera Administrative Region	119.63	92.27	1.30	Sufficient
Ilocos Region	238.64	88.31	2.70	Sufficient
Cagayan Valley	510.61	84.92	6.01	Sufficient
Central Luzon	185.01	87.61	2.11	Sufficient
CALABARZON	15.45	99.65	0.16	Insufficient
MIMAROPA	246.54	94.28	2.62	Sufficient
Bicol Region	138.24	106.63	1.30	Sufficient
Western Visayas	187.85	83.33	2.25	Sufficient
Central Visayas	19.34	103.61	0.19	Insufficient
Eastern Visayas	112.27	86.14	1.30	Sufficient
Zamboanga Peninsula	110.46	93.59	1.18	Insufficient
Northern Mindanao	103.25	94.81	1.09	Insufficient
Davao Region	58.46	95.36	0.61	Insufficient
SOCCSKSARGEN	160.21	103.70	1.54	Sufficient
Caraga Region	120.31	87.67	1.37	Sufficient
BARMM	123.16	84.69	1.45	Sufficient

Source: Authors' computation

Using the categorization presented in Table 4, we find that the high heel-shaped inflation responses of rice price inflation due to world rice prices are maintained (Figure 5). However, it is noticeable that the magnitude of the impact is significantly higher in rice-insufficient regions, where the immediate impact and peak are almost twice the value of their counterparts. The results confirm the assumption that adequate rice production and supply mitigate the inflationary impacts of increasing world prices (Figure 5). Conversely, the effect of a shock in ENSO on rice price inflation in rice-sufficient regions is twice that from rice-insufficient areas (last column, Figure 5). The figure shows that significant weather effects cause rice price inflationary pressure in regions relying on domestic rice production. Related to this, we find that a shock in world urea prices (column 1, Figure 5) has a lower immediate impact on rice price inflation in rice-sufficient regions. A plausible explanation is that rice-sufficient regions have heavy government intervention with fertilizer subsidies and/or vouchers in the major rice-producing regions. Lastly, we find that, similar to earlier results, the impact of fuel price inflation dissipates in only two to three months (column 2, Figure 5).

7. Conclusions

Our study employed a panel VAR method to investigate the effects of world rice prices, urea prices, fuel price inflation, and ENSO on rice price inflation in the Philippines. The study used a monthly panel dataset for the 17 regions in the Philippines from January 1994 to March 2023. The findings revealed that world rice prices, urea prices, fuel price inflation, and ENSO have had immediate positive impacts on rice price inflation and induced inflationary effects in rice prices of various magnitudes and persistence. Among all factors considered, the study found a larger and more persistent inflationary effect of world rice price shocks than of urea prices, fuel price inflation, and ENSO, and the impact lasted for six months. The effect of urea price shocks lasted six months, while the impact of fuel price inflation and ENSO shocks on rice price inflation lasted for three months. Further analysis of regional poverty incidence and self-sufficiency index subsamples revealed a similar pattern. Contrary to the assumption that inflationary factors are exacerbated in poor regions, the results showed lower impacts of world rice price and urea price shocks on rice price inflation in high-poverty areas. To explore the possibility that the results are due to the high incidence of poverty in rice-producing areas, rice self-sufficiency indices were computed for each region. Using rice self-sufficiency to create another subsample analysis revealed that the responses of rice price inflation due to world rice price shocks were almost twice those for rice-insufficient regions vis-à-vis rice self-sufficient regions. However, the response of rice price inflation due to climatic events such as ENSO shocks was significantly larger for rice-sufficient regions, where weather effects hampered rice production, than for rice self-insufficient regions.

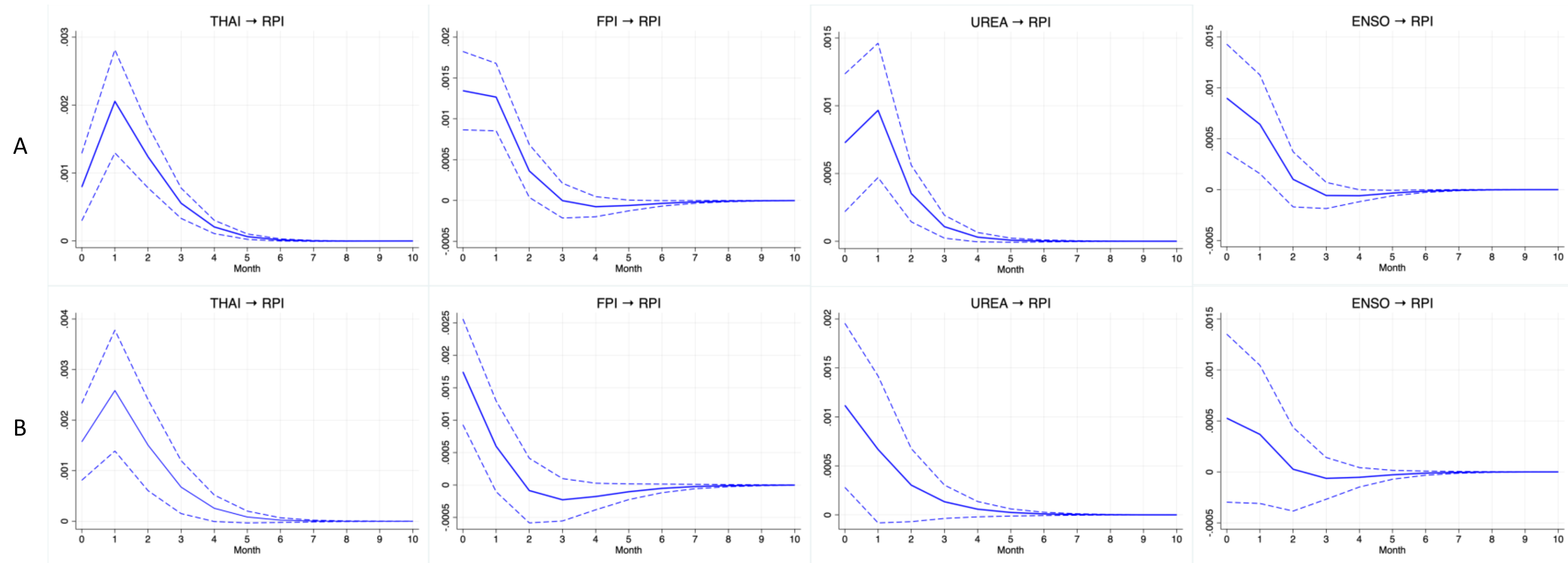


Figure 5. IRFs computed from estimated PVAR for (A) rice-sufficient and (B) rice-insufficient regions.

Four policy recommendations stem from the findings of our study. First, given that rice production has been shown to decrease inflationary pressure, especially shock from world rice markets, the Philippine government's existing support for rice farmers could be improved to boost rice production. The government could intervene with policies and programs, such as early seed distribution, improved irrigation facilities and management, promoting the adoption of hybrid rice varieties, increased subsidies for fertilizer and other inputs, and increased investment in agricultural research, development, and extension. Second, related to the previous point, improving connections between regions through constructing or improving road networks and communication technology (web-based information systems) would facilitate information flow and better movement of rice supply from rice-sufficient regions to rice-insufficient regions.

Third, given the factors affecting rice price inflation and the importance of rice as a staple in the Philippines, measures to decrease rice prices for consumers should be considered when inflation is deemed too high. To this end, policymakers could take action to lower import tariffs and taxes on rice, thus implementing consumer subsidies. Filipino farmers could benefit from improved marketing infrastructure, adding value chains for rice, and incentives to boost domestic rice production. Lastly, to effectively assess the rice inflation situation in the country for better policy action, investments should be made in improving rice price monitoring systems either by increasing investment in primary data collection and processing or exploring possibilities with machine learning to create predictive price models. Our study provides valuable information on the magnitude and persistence of the impacts of rice price food inflation drivers. The results also reinforce the importance of inflation data in guiding policymakers in addressing rising food prices. However, given the frequent movement of prices across time and the delay in the publication of inflation and price data, the use of new methodologies to collect data, such as the web-scraping technique used by Jaworski (2021), leads to a more robust analysis of inflation because of its timeliness and higher frequency of data. Given the usefulness of higher-frequency inflation data in capturing the impact of market and policy shocks, using more streamlined methods based on web-scraping, big data, and machine learning algorithms could be future avenues to explore.

References

Balié, J., Minot, N., & Valera, H. G. A. (2021). Distributional impacts of the rice tariffication policy in the Philippines. Economic Analysis and Policy, 69, 289-306.

Balié, J., & Valera, H. G. (2020). Domestic and international impacts of the rice trade policy reform in the Philippines. Food Policy, 92, 101876.

Bhattacharya, R., & Jain, R. (2020). Can monetary policy stabilise food inflation? Evidence from advanced and emerging economies. Economic Modelling, 89, 122-141.

Bordey, F. H., Castillo, G. T., Moya, P. F., & Padolina, W. G. (2016). Rice self-sufficiency under the lens of provincial analysis: A new way of looking at National Rice Security. National Academy of Science and Technology, Philippines.

BusinessWorld (2022). Rice prices set to rise as high input costs dampen farm output. Retrieved from https://www.bworldonline.com/economy/2022/09/28/477277/rice-prices-set-to-rise-as-high-input-costs-dampen-farm-output/.

Cao, J., Zhang, Z., Tao, F., Chen, Y., Luo, X., & Xie, J. (2023). Forecasting global crop yields based on El Niño Southern Oscillation early signals. Agricultural Systems, 205, 103564.

Chau, N. T., & Ahamed, T. (2022). Analyzing factors that affect rice production efficiency and organic fertilizer choices in Vietnam. Sustainability, 14(14), 8842.

Dawe, D., & Kimura, S. (2023). Mitigating emerging food security risks in rice markets. Development Asia. Retrieved from https://development.asia/insight/mitigating-emerging-food-security-risks-rice-markets.

Durevall, D., Loening, J. L., & Birru, Y. A. (2013). Inflation dynamics and food prices in Ethiopia. Journal of Development Economics, 104, 89-106.

Hammoudeh, S., Nguyen, D. K., & Sousa, R. M. (2015). US monetary policy and sectoral commodity prices. Journal of International Money and Finance, 57, 61-85.

Hebebrand, C., & Glauber, J. W. (2023). The Russia-Ukraine war after a year: Impacts on fertilizer production, prices, and trade flows. In: Glauber, J., & Laborde Debucquet, D. (Eds.), The Russia-Ukraine Conflict and Global Food Security; Section One: A conflict with global consequences. Washington, DC: International Food Policy Research Institute. pp. 43-47.

Iddrisu, A. A., & Alagidede, I. P. (2020). Monetary policy and food inflation in South Africa: A quantile regression analysis. Food Policy, 91, 101816.

Jaworski, K. (2021). Measuring food inflation during the COVID-19 pandemic in real time using online data: a case study of Poland. British Food Journal, 123(13), 260-280.

Liaqat, Z. (2019). Does government debt crowd out capital formation? A dynamic approach using panel VAR. Economics Letters, 178, 86-90.

Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. The Quarterly Review of Economics and Finance, 46(2), 190-210.

Lin, F., Li, X., Jia, N., Feng, F., Huang, H., Huang, J., Fan, S., Ciais, P., & Song, X. P. (2023). The impact of Russia-Ukraine conflict on global food security. Global Food Security, 36, 100661.

Mottaleb, K. A., Kruseman, G., & Snapp, S. (2022). Potential impacts of Ukraine-Russia armed conflict on global wheat food security: A quantitative exploration. Global Food Security, 35, 100659.

National Economic and Development Authority (2022). Rice Tariffication Law is the best model that we have to help both farmers and consumers — NEDA. Retrieved from https://neda.gov.ph/rice-tariffication-law-is-the-best-model-that-we-have-to-help-both-farmers-and-consumers-neda/.

Nguyen, A. D., Dridi, J., Unsal, F. D., & Williams, O. H. (2017). On the drivers of inflation in Sub-Saharan Africa. International Economics, 151, 71-84.

Poursina, D., Schaefer, K. A., Hilburn, S., & Johnson, T. (2023). Economic impacts of the Black Sea Grain Initiative. Journal of Agricultural Economics. DOI:10.1111/1477-9552.12549.

Shan, L. Y. (2023). India's rice export ban to hurt millions globally. These countries will be the worst hit. CNBC. Retrieved from https://www.cnbc.com/2023/08/02/indias-rice-export-ban-to-impact-millions-in-asia-africa-middle-east.html.

Shen, X., Holmes, M. J., & Lim, S. (2015). Wealth effects and consumption: a panel VAR approach. International Review of Applied Economics, 29(2), 221-237.

Shively, G., & Thapa, G. (2017). Markets, transportation infrastructure, and food prices in Nepal. American Journal of Agricultural Economics, 99(3), 660-682.

Termos, A., Naufal, G., & Genc, I. (2013). Remittance outflows and inflation: The case of the GCC countries. Economics Letters, 120(1), 45-47.

Tule, M. K., Salisu, A. A., & Chiemeke, C. C. (2019). Can agricultural commodity prices predict Nigeria's inflation? Journal of Commodity Markets, 16, 100087.

Ubilava, D. (2017). The ENSO effect and asymmetries in wheat price dynamics. World Development, 96, 490-502.

Ubilava, D., & Abdolrahimi, M. (2019). The El Niño impact on maize yields is amplified in lower income teleconnected countries. Environmental Research Letters, 14(5), 054008.

United States Department of Agriculture (2023). Production, supply, and distribution. Retrieved from https://apps.fas.usda.gov/psdonline/app/index.html#/app/advQuery.

Valera, H. G., Balié, J., & Magrini, E. (2022). Is rice price a major source of inflation in the Philippines? A panel data analysis. Applied Economics Letters, 29(16), 1528-1532.

Wu, X., & Xu, J. (2021). Drivers of food price in China: a heterogeneous panel SVAR approach. Agricultural Economics, 52(1), 67-79.

Zhang, C., Meng, C., & Getz, L. (2014). Food prices and inflation dynamics in China. China Agricultural Economic Review, 6(3), 395-412.