The changing effect of commodity prices and remittances on inflation: Evidence from the Philippines

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Abstract

This study examines inflation dynamics in a net food and energy importer and remittances recipient economy, focusing on the effects of rice and fuel prices under inflation targeting and rice tariffication regimes. We employ quantile regression models on monthly provincial panel data from the Philippines over the period 1996-2024. The findings indicate that the impact of rising rice and fuel prices is greater during periods of high inflation. Indeed, this finding is verified with data from Indonesia, Thailand and India. We also find that inflation targeting and rice tariffication in the Philippines mitigate these effects, with high-poverty and rice-deficit regions showing a more pronounced reduction in the rice inflation effect after the rice tariffication. In addition to this, we also examine remittances and find a nonlinear influence on overall inflation in the Philippines and an asymmetric effect in the other three countries.

Keywords

Inflation
Commodity prices
Inflation targeting
Rice tariffication
Remittances
Quantile regression
Panel data

JEL Classification

C33
E43

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1. Introduction

Emerging markets have experienced some of the highest inflation rates worldwide in recent years. Accordingly, there is renewed interest in how commodity price fluctuations affect inflation across different economic conditions. Such discussion has gained strength especially in emerging market countries that are net importers of energy and major staple commodities. While most literature on the sensitivity of inflation to its determinants focuses on diverse inflation environments (Abbas and Lan 2020; Dao et al. 2024; Ge and Sun 2024; Hwang and Zhu 2024), other studies consider the role of regional heterogeneity in explaining such relationship (Fitzgerald et al. 2024; Iddrisu and Alagidede 2021). Indeed, Fitzgerald et al. (2024) warn that the neglect of regional heterogeneity can obscure the true relationship in aggregate analyses, especially when central banks adjust policies to meet inflation targets. Yet, literature on the regional dynamics underpinning this linkage is thin. Moreover, the impact of prices of major commodities within this regional context has received limited attention in emerging markets.

With this background, the objective our study is to conduct an empirical investigation of the effects of rice and fuel prices on overall inflation in the Philippines. We also extend our empirical analysis to Indonesia, Thailand and India. The empirical analysis is based on a unique monthly provincial or state panel data. Indeed, there is a shortage of prior investigation of regional inflation dynamics within a panel setting, especially during periods of commodity price shocks-induced inflation or after changes monetary or food policies, as the availability of data on sub-national inflation and determinants is typically scattered from various sources. We resolve this critical limitation by organizing inflation and commodity price data from the database managed by the Philippine Statistics Authority, Badan Pusat Statistik, and the Bank of Thailand. The mandates of these agencies include, among others, monitoring of prices and availability of essential commodities. For India, we rely on private database called Dataful, whose data compilation is also based on official sources. All told, the salient feature of these databases is that they collect monthly inflation and commodity price data for different provinces or states with sufficiently long observations.

This unique monthly provincial or state panel dataset allows us to contribute to the literature by answering two key research questions. First, is there evidence supporting whether the impact of rice and fuel price inflation is greater during times of higher overall inflation? Second, to what extent do inflation targeting and rice tariffication policy alter the effect of rice and fuel price inflation? To this end, we use Machado and Silva's (2019) fixed effects quantile regression model to estimate conditional inflation quantiles. A key advantage of this methodology is its ability to control for unobserved heterogeneity, allowing individual effects to influence the entire distribution of the dependent variable—not just its mean. This enhances the robustness of our estimates, particularly with respect to endogeneity concerns. Using this approach also enables us to interpret our results through the theoretical framework of price-setting behavior (Taylor 2000; Golosov and Lucas 2007).

The current study also offers policy perspectives to further our understanding of the consequences the monetary or food policy. The combination of such policy angles is often overlooked in studies of regional inflation dynamics. Specifically, we connect our findings to key policy interventions such as the inflation targeting framework introduced in 2002 and rice tariffication policy implemented in 2019. Inflation targeting appears to mitigate the inflationary effects of fuel price shocks. Meanwhile, rice tariffication–the shift from quantitative restrictions on rice imports to a tariff only system–helps reduce inflation by lowering rice prices through increased private sector imports. By capturing these policies alongside rice and fuel price changes, we offer valuable insights into how such factors may influence inflation dynamics. According to Liu and Serletis (2025), energy and agricultural commodity prices also remain critical concerns for policymakers and researchers alike. Thus, monitoring the prices of those items can provide essential guidance for policy adjustments in response to evolving market conditions.

We also make further contribution to the literature by examining the differential effects of rice and fuel prices on overall inflation before and after rice tariffication, focusing on provinces with varying levels of rice self-sufficiency and poverty. Applying Deaton's (1989) net benefit ratio and nationally representative data to estimate provincial rice production and consumption, we offer complementary information to monthly panel data analysis. That is, we examine how rice and fuel prices affect household inflation expectations due to their salience. This hypothesis is tested through a simple correlation analysis between provincial inflation expectations and rice or fuel prices using quarterly consumer expectations survey data. Such dataset is important for central banks to achieve their objective of publishing official statistics on household inflation expectations and for managing such expectations.

Finally, we broaden the scope by comparing our findings with panel data from Indonesia, India and Thailand. This comparison sheds light on how rice prices affect inflation in traditional rice importers like Indonesia and the Philippines, versus major exporters such as India and Thailand. We also employ a proxy for monthly sub-national data on remittances to align with prior research on Philippine inflation (Lartey 2016; Valera et al. 2022). This allows us to better analyze how remittance-driven real wealth boosts consumption and inflation.

The results can be summarized as follows. This paper shows that rising fuel and rice inflation has a more significant impact during periods of high overall inflation. Still, this effect is significantly lessened by inflation targeting and rice tariffication. After tariffication, a significant drop in the effect of rice price inflation is observed in high-poverty and rice-deficit areas. We also find nonlinear effect of remittances on overall inflation in the Philippines and an asymmetric effect in the other three Asian economies.

The remainder of the paper is structured as follows. Motivating literature is discussed in Section 2. Section 3 presents the methodology and data. Empirical evidence on the impact of rice and fuel prices and remittances on inflation is presented in Section 4. Section 5 concludes.

2. Related literature

Our paper is related to three strands of research. The first literature examines the state-dependent effects of oil and food prices on domestic inflation. In terms of theories, our starting point is motivated by a rich literature that uses insights about price-setting behavior in different inflation environments. The theories suggested by Golosov and Lucas (2007), Costain and Nakov (2011), and Devereux and Siu (2007) connect with the theoretical interpretations we provide for our findings.

Recent examples include Bareith and Ferto (2024), Ge and Sun (2024), Iddrisu and Alagidede (2020, 2021) and Mahmoudinia (2021). Most of these studies either focus on analyzing national-level overall inflation or food inflation. Iddrisu and Alagidede (2020) and Ge and Sun (2024) examine the impact of monetary policy and oil prices on overall inflation. Iddrisu and Alagidede (2021) analyze the impact of monetary policy on inflation for individual provinces in Ghana. Recent studies also use a quantile-based method but focus on cross-country analysis of inflation at risk (Banerjee et al. 2024). In addition to this, several studies have highlighted the significant role of food prices in driving inflation in emerging and developing economies (Durevall, Loening and Birru 2013). Our main departure from these studies is the analysis of the effects of rice and fuel prices on provincial overall inflation using a panel quantile regression.

The second strand of literature includes works in monetary policy that investigate the effects of inflation targeting on inflation. For instance, Sethi and Mishra (2024) examine the effects of inflation targeting on 24 Asian economies and find that such a policy regime reduces inflation's level and volatility, especially during the Global Financial Crisis. However, it appears that inflation targeting affects only the inflation rate but not its volatility during the Covid-19 pandemic. Hwang and Zhu (2024) also examine the effects of an inflation-targeting regime and consider a cross-country analysis of the state-dependent effect of oil price shocks on inflation. They find that while inflation targeting helps to shorten the duration of inflation that exceeds the upper limit of the inflation target caused by oil price shocks, it does not significantly reduce the level or volatility of inflation. This result aligns with Aharon, Aziz and Kallir (2023), who find that structural oil supply shocks have little to no impact on inflation for most ASEAN5+3 countries. Relative to these papers, we examine the consequences of both the monetary policy shift to inflation targeting and change in food policy through the implementation of the rice tariffication policy. This is the first paper that explains the overall inflation differential across provinces and considers its dynamics under those two policy regimes.

The third strand of literature we contribute to is concerned with regional analysis of inflation dynamics. A recent notable example is Fitzgerald et al. (2024) who use city- and state-level data to identify the structural relationship between the US unemployment and inflation. A particularly closely related paper to ours is Valera, Balié, and Magrini (2022), who analyze regional monthly inflation dynamics in the Philippines using a panel vector auto-regression model from 2007 to 2019. They find that the effect of rice prices on inflation is more significant than that of fuel prices and remittances. In the context of Ghana, Iddrisu and Alagidede (2021) use a quantile method and find that restrictive monetary policy delivers stability in prices in some provinces, but prices in other locations are destabilizing. Another related study is Choi, Lee, and O'Sullivan (2016), who examine the impact of inflation targeting on the inflation level and volatility across South Korean cities. Our findings contribute to the existing literature by presenting drivers of geographically disaggregated inflation in the Philippines and in other selected emerging markets in Asia.

3. Estimation methodology and data

The main objective of this section is to outline the fixed effects quantile regression methodology. Next, we document three distinct datasets. The first is sub-national level data on overall inflation and its drivers in the Philippines and other Asian countries for international comparison. The second is provincial remittance proxy data based on publicly available overseas workers' and national-level surveys. The third is provincial data on net benefit ratio. This latter dataset, estimated from a nationally representative household survey data and microsimulation, enable us to report results across different provinces based on their rice self-sufficiency levels.

3.1. Estimation methodology

In this section, we outline the estimation methodology used to analyze the inflation process in the economy. We begin with a reduced-form model that links inflation to commodity prices as specified in Eq. (1):

$$\pi_t = \alpha + \beta \Delta c_t + \lambda \pi_{t-1} + \varepsilon_t. \tag{1}$$

Here, π_t denotes overall domestic inflation, $\Delta c_t$is the percentage change in commodity price variables and, ε_t is the error term. This reduced-form approach follows Gerlach and Stuart (2024).

Recognizing the importance of price frictions that can potentially display in an economy comprised of geographically dispersed regions, we estimate our model using panel data from Philippine provinces, all of which are subject to the same monetary and food policies. To capture how the sensitivity of inflation to commodity price changes varies across different inflationary environments, we employ the fixed effects quantile regression method of Machado and Silva (2019). The model applied to provincial inflation data is specified as follows:

$$\pi_{i,t,m} = \alpha_{i,\tau} + \beta_{1,\tau} \Delta c_{i,t,m}^{rc} + \beta_{2,\tau} \Delta c_{i,t,m}^{fu} + \sum_{k=1}^{n} \lambda_{\tau,k} \pi_{i,t,m-k} + \gamma_t + \delta_i + \varepsilon_{\tau,i,t,m}. \tag{2}$$

In this equation, $\pi_{i,t,m}$ is the monthly year-on-year change in the general consumer price index (CPI) for province *i*, year *t*, and month *m*. The variables $\Delta c_{i,t,m}^{rc}$ and $\Delta c_{i,t,m}^{fu}$ are the respective changes in rice and fuel prices. The parameters $\alpha_{i,\tau}$, $\beta_{1,\tau}$, $\beta_{2,\tau}$ and $\lambda_{\tau,k}$ are to be estimated; γ_t denotes year fixed effects; δ_i

captures time-invariant province-specific effects; and $\varepsilon_{\tau,i,t,m}$ is the error term, assumed to have a conditional expectation of zero at each quantile. The index k indicates the number of lags included.

To facilitate comparison with previous studies on Philippine regional inflation (Valera, Balié, and Magrini 2022), we also include remittances as an explanatory variable. Lags of rice prices, fuel prices, and remittances are incorporated to assess their long-run effects on inflation.

Our main fixed effects quantile regression is thus specified as follows:

$$\pi_{i,t,m} = \alpha_{i,\tau} + \beta_{1,\tau}\Delta c_{i,t,m}^{rc} + \beta_{2,\tau}\Delta c_{i,t,m}^{fu} + \beta_{3,\tau}\Delta c_{i,t,m}^{re} + \sum_{k=1}^{n} \lambda_{\tau,k}\pi_{i,t,m-k} + \sum_{k=1}^{n} \theta_{\beta_j,\tau,k}\, Z_{i,t,m-k} + \gamma_t + \delta_i + \varepsilon_{\tau,i,t,m}. \tag{3}$$

Here, the additional explanatory variable $\Delta c_{i,t,m}^{re}$ is the change in remittances, and $Z_{i,t}$ includes lagged values of rice prices, fuel prices and remittances. The subscript j refers to β coefficients associated with commodity price and remittance variables.

In addition to estimating Eq. (3) on the entire sample, we conduct separate estimations for periods before and after (i) the adoption of inflation targeting and (ii) the implementation of rice tariffication. This allows us to explore the effects of these policy changes and their links to poverty and rice sufficiency. For all analyses, we estimate coefficients for nine quantiles τ: the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles. Confidence intervals are calculated using clustered standard errors at the province level with 1,000 bootstrap replications.

As mentioned earlier, one major benefit of the fixed effects quantile regression methodology is that it accounts for unobserved differences across individuals, letting these effects shape the whole distribution of the dependent variable rather than just its average. This enhances the robustness of our estimates, particularly with respect to endogeneity concerns. Nevertheless, reverse causality remains a potential issue, as overall inflation could influence rice or fuel prices. To mitigate this, we follow Choi et al. (2018) by including lagged values of inflation and commodity prices as instruments.

Another identification issue that needs to be discussed before estimating Eq. (3) is the omitted variables that may be correlated with both inflation and the explanatory variables. To address this, we follow first the argument of Molyneux et al. (2022) for the inclusion of time-fixed effects, such as the vector γ_t in Eq. (3). Adding year fixed-effects controls for factors common to all provinces on a given year, such as global commodity price shocks affecting both domestic prices and inflation or government policies beyond the ones under review, including taxes and subsidies. We also re-estimate Eq. (3) in our robustness analysis to further reduce concerns about omitted variables by capturing the impact of global commodity price shocks through the inclusion of the Thailand 5% broken rice export prices to.

In the above regression, each of the β coefficients measures the short-run impact of of rice prices, fuel prices, and remittances. With these coefficients at hand and the corresponding coefficients of their lagged values $\theta_{\beta_j,\tau,k}$, the long-run effect of each driver can be computed for each quantile τ:

$$LRE = \frac{\beta_k + \left(\sum_{k=1}^{n} \theta_{\beta_j,\tau,k}\right)}{1 - \left(\sum_{k=1}^{n} \lambda_{\tau,k}\right)}. \tag{4}$$

In Eq. (4), the estimated long-run effect is a crucial metric for assessing how the sensitivity of inflation to rice and fuel prices varies between the lower and higher quantiles. That is, it allows us to determine whether the impact of these drivers is greater at higher quantiles of inflation.

3.2. Philippine data

Monthly observations of the overall CPI for 74 sample provinces are obtained from the Philippine Statistics Authority (PSA). Figure 1 displays the list of sample provinces and average overall inflation rate. We include the National Capital Region (NCR) in our sample as it is the only region in the country composed of highly urbanized areas, including the capital Metro Manila, rather than provinces. NCR also contributes one-fifth of the national CPI basket. Thus, some of the mechanisms that may underpin the relationship of inflation across different areas in the Philippines may operate in this region. The sample provinces were selected based on the availability of panel data for the main variables over sufficiently long period, spanning from August 1996 to April 2024, yielding 342 time observations for each province. This enables us to offer a more granular scope of geographical locations within a country compared with existing literature that focuses on individual country analysis of inflation dynamics using aggregate data.

The study period captured strong fluctuations and spikes, as well as significant shifts to inflation targeting and rice tariffication. Figure 1 highlights noticeable differences in provincial inflation rates over the sample period. Inflation rates have fluctuated between 3.8% for Bulacan and Ilocos Norte and 5.4% for Bukidnon and Maguindanao. This clearly constitutes a substantial difference relative to the mean inflation rate across provinces. Many provinces exhibited consistently high or low inflation rates, reflecting deviations above the national inflation target set for a given year.

We also capture the remittance effect by including a proxy for provincial remittance data. As only national-level monthly remittance data are available from the Bangko Sentral ng Pilipinas, we use annual remittance data from survey of overseas Filipino (SOF) workers from 1995 to 2012. From SOF, yearly provincial and regional data are available from 1995 to 2001 and 2002 to 2012, respectively. We use provincial population data for the latter period as a proxy to estimate provincial shares.

Next, we interpolate the annual series to monthly frequency using Silva and Cardoso's (2001)[1] methodology. We normalize this interpolated series by aligning the total remittances across all provinces with the national-level monthly remittance data. For 2013-2024, we use quarterly provincial savings

[1] Li (2023) employed a similar approach in interpolating official annual immigration data to quarterly frequency.

deposit data, which are interpolated into monthly observations. Then, we obtain percent changes and apply these to extending the proxy for monthly data from 2012 to the series starting in 2013.

Figure 1. Average overall inflation rate by province, 1996-2024.
Inflation data come from the Philippine Statistics Authority.

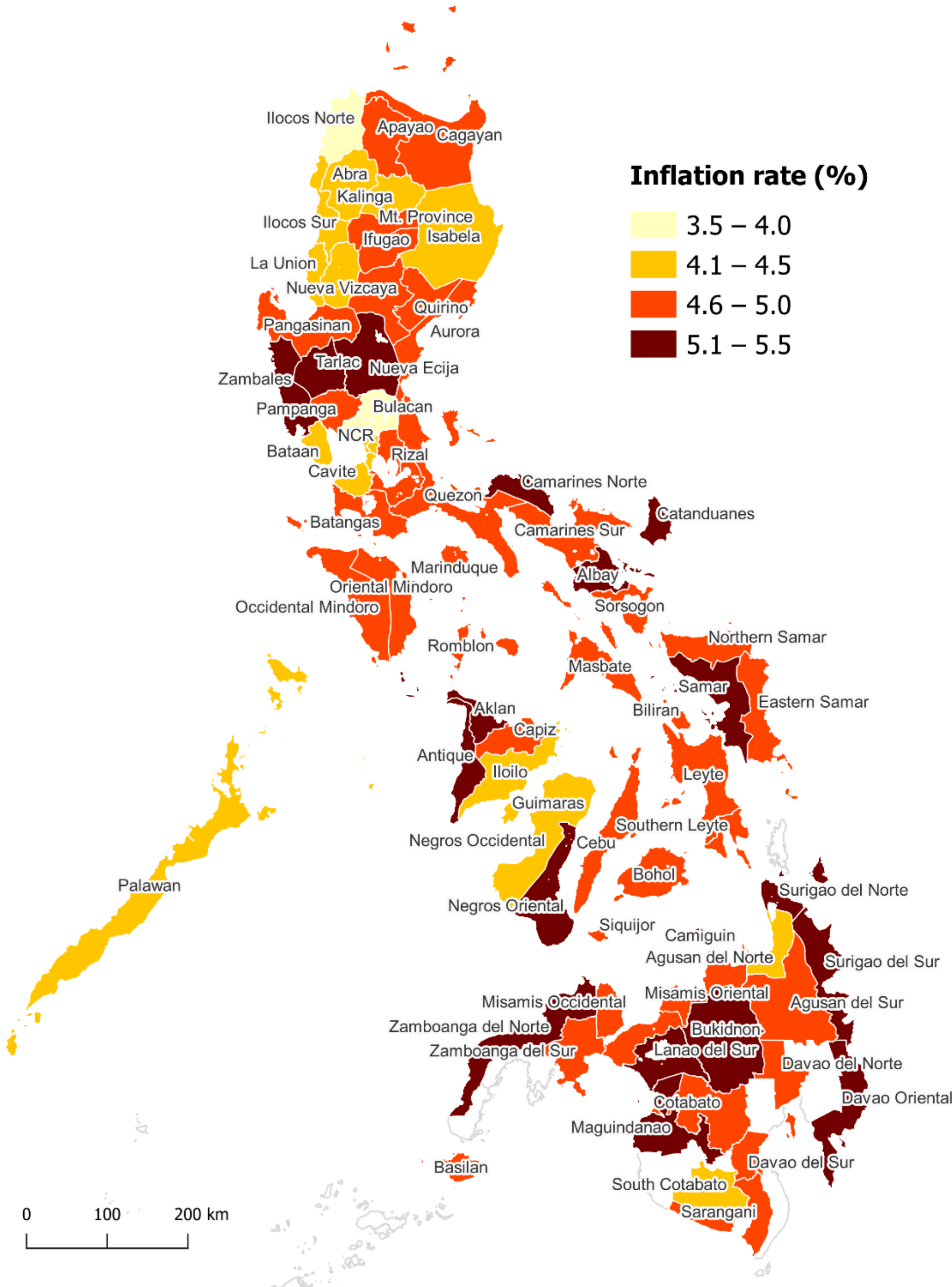


Figure 2 illustrates the evolution of the cross-sectional mean of inflation over nearly three decades. Inflation generally exceeded 4% before 2002. After the monetary policy shift to inflation targeting in 2002, the central bank delivered low and stable inflation over the next 29 months, oscillating between 2% and 3%. While such a monetary policy regime managed to keep inflation within the 2-4%

range for much of 2004-2024, inflation was characterized by fluctuations and spikes, driven by supply-side factors. Notably, inflation spikes in December 2004, August 2008, October 2018, and February 2023 were largely driven by the sharp increase in the prices of food and energy-related CPI components. In particular, the 2008 food inflation was due to the rice price crisis, while the 2018 surge can be attributed to the short-run effects of typhoons that disrupted rice production in major rice-producing provinces.

Figure 2. Evolution of provincial overall inflation and rice and fuel price inflation, 1996-2024. Inflation data come from the Philippine Statistics Authority.

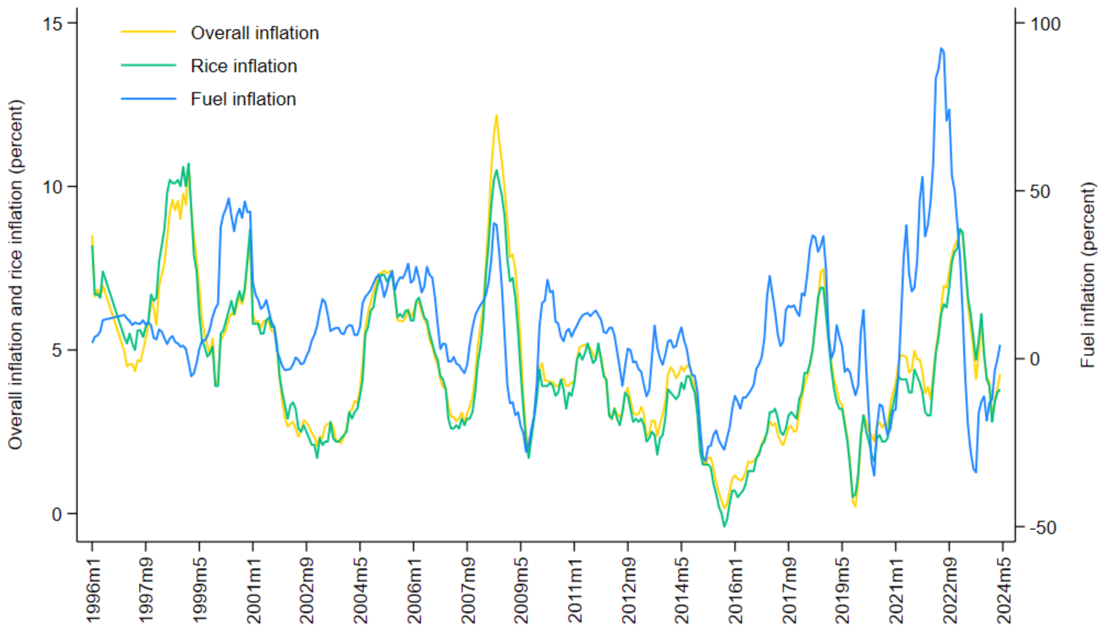


Figure 2 also displays the relationship between overall inflation and rice or fuel inflation over the August 1996-April 2024 period. The figure indicates that rice and fuel price inflation has generally moved in the same direction as overall inflation. Table 1 also quantifies such a co-movement in terms of simple correlation coefficients between these inflation series. It shows that overall inflation is positively and significantly correlated with rice prices; $\rho = 0.98$ ($p < 0.01$). Similarly, the correlation between overall inflation and diesel prices is positive and significant; $\rho = 0.46$ ($p < 0.01$). In line with the conventional wisdom and considering the weights of rice and fuel prices in the CPI basket, the results motivate the possibility that a rise in rice or fuel prices is an important driver of the inflation process in the Philippines.

A discernable pattern emerges in the movements between overall inflation and rice price series: (a) rising overall inflation is typically preceded by increases in rice price inflation, while (b) periods of falling overall inflation tend to coincide with decreases in rice prices. A milestone event that contributed to the fall in rice price inflation occurred in March 2019 with the implementation of the rice tariffication policy. This policy enabled the Philippine government to remove quantitative restrictions on rice imports and replace them with applied tariffs[2].

Table 1. Correlation among overall inflation, rice or fuel price inflation.

	Inflation	Rice	Diesel	Gasoline
Inflation	1.00			
Rice	0.98*** (0.000)	1.00		
Diesel	0.46*** (0.000)	0.45*** (0.000)	1.00	
Gasoline	0.50*** (0.000)	0.50*** (0.000)	0.94*** (0.000)	1.00

Notes: *** $p < 0.01$. Figures in parentheses are *p*-values.

3.3. International comparison data

To extend our analysis beyond panel quantile regression in the Philippine context, we offer a comparison with matching estimates from India, Indonesia, and Thailand. This comparison serves three principal purposes. First, it deepens our understanding of sub-national inflation dynamics in major rice-importing countries, such as the Philippines and Indonesia, as well as in large rice exporters like India and Thailand. We estimate quantile panel regression models for each country using data from January 2015 to April 2024. The sample period is determined by the availability of consistent sub-national data. Our analysis includes 34 provinces in Indonesia and 74 provinces in Thailand. The Indonesian data are sourced from its national statistical agency, Badan Pusat Statistik. Data for Thailand are from the Bank of Thailand. For India, we estimate the quantile panel model using data from 30 states collected from the private database Dataful. In Appendix Figure A1, we provide the list of these sample provinces or states from Indonesia, Thailand and India and overlay their average overall inflation rates during the sample period.

Second, inflation targeting has been in place in those countries, with Thailand adopting it in May 2000, the Philippines in January 2002, Indonesia in July 2005, and India in May 2016. Third, we select those countries to represent the wider set of emerging markets with large values of remittances in terms of dollar amount, as reported in Table 2. In terms of remittance data for India, Indonesia and Thailand, we use a similar approach to the one considered for the Philippines with respect to using sub-national annual population data as a proxy to estimate the shares of remittances across provinces or states. We also apply Silva and Cardoso's (2001) approach in interpolating annual population data into monthly frequency.

[2] The applied tariff rates are: (a) a 35% tariff for both in- and out-quota rice imports from ASEAN member states, (b) a 40% in-quota tariff for rice imports from non-ASEAN and World Trade Organization (WTO) member states within the minimum access volume (MAV) of 350,000 metric tons, (c) a 50% out-quota tariff for imports from non-ASEAN and WTO member states above the MAV, and (d) a 180% bound tariff rate for imports from non-ASEAN countries above 350,000 metric tons (Balié, Minot and Valera 2021).

Table 2. Size of remittance inflows in 2023.

Country	Value (USD billion)	Share of GDP (%)
India	119.5	3.4
Indonesia	14.5	1.1
Philippines	39.1	8.9
Thailand	9.6	1.9
Mean	45.7	3.8
Aggregate	182.7	

Source: World Bank (2023).

4. Empirical results

This section discusses the fixed effect quantile regression results. Our aim is to examine whether changes in fuel prices, rice prices, and remittances constitute a factor that helps explain the dynamic behavior of overall inflation rates across provinces.

4.1. Fixed effects quantile regression results

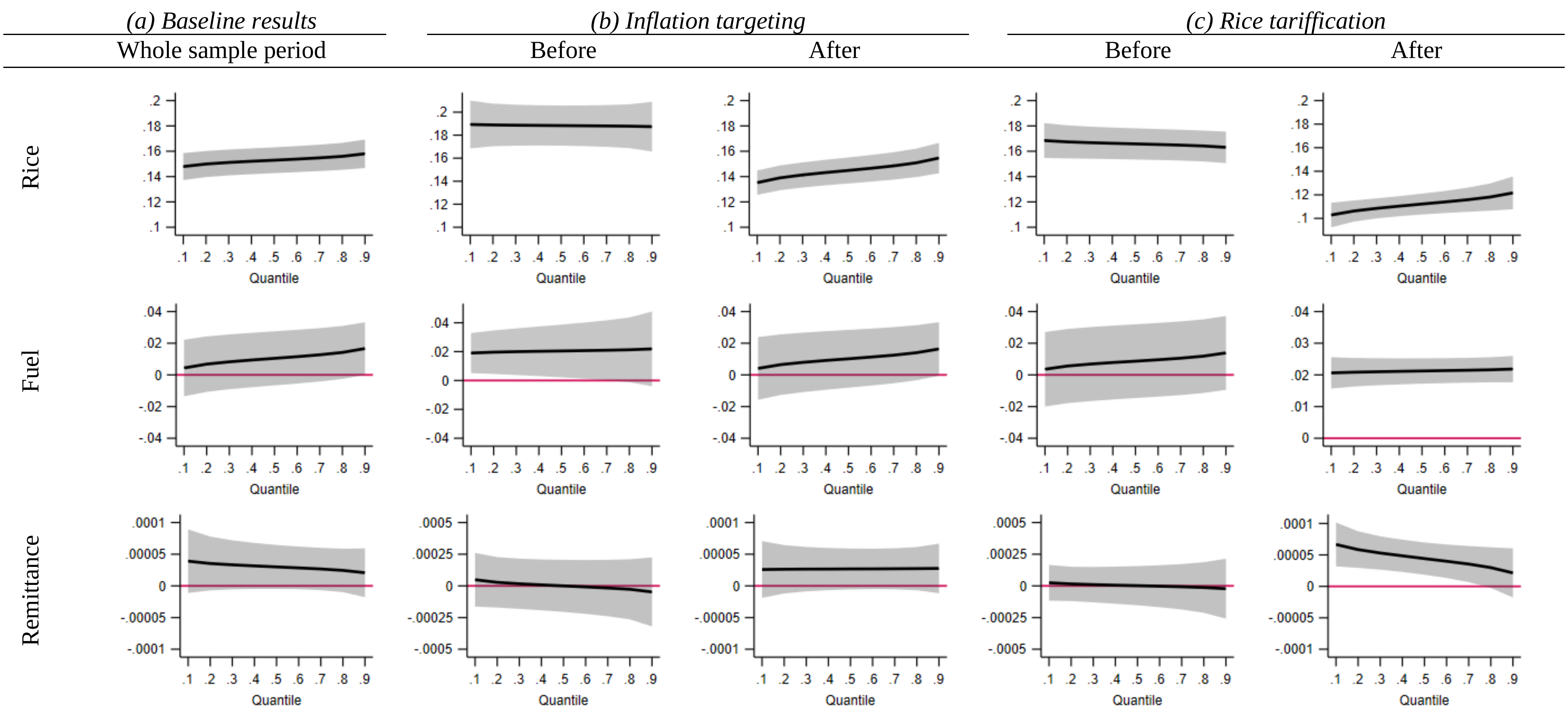
Figure 3 shows the baseline estimates derived from Eq. (3) using the full dataset, alongside a comparative analysis of sub-sample estimates before and after the implementation of inflation targeting and rice tariffication. The black solid line represents the point estimate, while the gray shaded area denotes the associated 95% confidence interval. For comprehensive insights, Table 3 provides complete regression results, including coefficients for the lagged explanatory variables and overall inflation.

As illustrated in Figure 3a, a key insight from the fixed effects quantile regression model is the strong positive relationship between overall inflation and both rice and fuel price inflation. The impact of rising rice prices is statistically significant across all quantiles, while the effect of fuel prices becomes significant only at the higher quantiles.

In the short run, our estimates indicate that a 1% increase in rice prices corresponds to a 0.15% increase in overall inflation at the lowest quantile and a 0.16% at the highest quantile. For fuel, where the short-run effect is significant, a 1% increase in its prices results in a 0.01% rise in overall inflation at $\tau = 0.8$ and $\tau = 0.9$. These findings suggest that the effects of rice and fuel prices tend to increase at higher quantiles. In other words, when inflation is already elevated, increases in rice and fuel prices have a more pronounced impact.

It is important to highlight that overlapping confidence intervals can be seen for both the full sample and the sub-sample estimates overlap. For instance, the short-run effect estimates for $\beta_{1,\tau}$ and $\beta_{2,\tau}$ increase with τ in the cases of rice and fuel inflation but the upper bound of the confidence interval at $\tau = 0.1$ fits inside the $\tau = 0.9$ confidence band. This overlap indicates that there is no statistically significant difference in the short-run effects of rice or fuel inflation between the lower and upper quantiles.

Figure 3. Fixed effects quantile regression results for the whole sample and during inflation targeting and rice tariffication periods.



Note: Gray shaded area is the 95% confidence interval around the point estimates.

Table 3. Estimated panel quantile regression coefficients for the whole sample period.

		τ								
Variables	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Rice price inflation	0.1530***	0.1479***	0.1499***	0.1511***	0.1521***	0.1529***	0.1538***	0.1548***	0.1560***	0.1580***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fuel price inflation	0.0105***	0.0044	0.0068	0.0083	0.0094	0.0105	0.0115	0.0127	0.0142*	0.0167**
	(0.000)	(0.631)	(0.446)	(0.349)	(0.282)	(0.229)	(0.183)	(0.139)	(0.096)	(0.049)
Changes in remittances	0.00003*	0.00004	0.00003	0.00003*	0.00003*	0.00003*	0.00003*	0.00003	0.00002	0.00002
	(0.070)	(0.127)	(0.102)	(0.092)	(0.088)	(0.090)	(0.098)	(0.117)	(0.162)	(0.289)
Rice price inflation (*t* - 1)	-0.1432**	-0.1324***	-0.1365***	-0.1390***	-0.1409***	-0.1427***	-0.1445***	-0.1465***	-0.1490***	-0.1532***
	(0.040)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fuel price inflation (*t* - 1)	-0.0021***	0.0048	0.0021	0.0005	-0.0007	-0.0019	-0.0030	-0.0043	-0.0060	-0.0087
	(0.000)	(0.531)	(0.783)	(0.947)	(0.926)	(0.813)	(0.706)	(0.595)	(0.472)	(0.312)
Changes in remittances (*t* - 1)	0.0001***	0.0000	0.0000	0.0000	0.0000*	0.0001**	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.866)	(0.480)	(0.182)	(0.062)	(0.018)	(0.004)	(0.001)	(0.000)	(0.000)
Overall inflation (*t* - 1)	0.9191***	0.8509***	0.8772***	0.8930***	0.9053***	0.9166***	0.9279***	0.9407***	0.9567***	0.9832***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.2292***									
	(0.000)									
Observations	24,568	24,568	24,568	24,568	24,568	24,568	24,568	24,568	24,568	24,568
R-squared	0.909									

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Figures in parentheses are *p*-values.

However, a particularly insightful finding emerges from the long-run effect estimates, which provide quantitative evidence that the sensitivity to rice and fuel price changes remains higher at the upper quantiles. Specifically, by substituting the short-run impact estimates and the relevant coefficients for the lagged values of rice prices and overall inflation into Eq. (4) from Section 3.1, we estimate the long-run effect to be 0.1040 at $\tau = 0.1$ and 0.2857 at $\tau = 0.9$ for rice prices. The sensitivity to fuel prices also increases notably at higher quantiles, with a long-run effect of 0.0617 at $\tau = 0.10$ compared to 0.4762 at $\tau = 0.9$.

Overall, these empirical results align with previous research, which highlights the importance of accounting for asymmetries and fat tails in the distribution of inflation when analyzing the roles of food and energy prices. Such modeling is crucial for understanding the dynamics of inflation and commodity prices (Abbas and Lan 2020; Choi et al. 2018; Ge and Sun 2024; Iddrisu and Alagidede 2021).

One can also consider several theoretical explanations for our key finding that rising rice or fuel prices have a greater impact during times of higher inflation. For instance, Taylor (2000) argues that firms are more likely to pass on their increased costs to consumers in an inflationary environment. Similarly, Golosov and Lucas (2007) propose a state-dependent pricing model and suggest that while firms often display price rigidity, the urgency to adjust prices during high inflation typically outweighs their reluctance to make frequent changes. Devereux and Siu (2007) further contribute to this discussion by noting that firms tend to be more averse to underpricing than to overpricing their goods. Building on these insights, Costain and Nakov (2011) argue that firms with lower adjustment costs are better equipped to respond to inflationary pressures by changing their prices.

Taken together, these economic rationales help explain our empirical findings: when inflation is elevated, firms tend to adjust their prices more rapidly, making it more likely that increases in rice and fuel costs are passed on to consumers. In other words, higher inflation prompts larger and more frequent price responses from firms that are able to adjust prices within each period.

We also examine the impact of remittances on inflation. As illustrated in Figure 3a, remittances are associated with an increase in overall inflation between the 20th and 60th quantiles. This observation aligns with economic theory. Large inflows of remittances, when converted into domestic currency, expand the money supply and boost household consumption. If these funds are not directed toward productive investments or capital formation, the resulting increase in consumption can drive inflation higher (Narayan, Narayan, and Mishra 2011). Remittances also enhance real wealth, further stimulating consumption and creating short-run excess demand that pushes up prices.

However, the inflationary impact of remittances is not always straightforward. Rivera and Tullao (2020) suggest that remittance inflows do not necessarily lead to inflation. If these funds are allocated to savings, investment, or sectors with ample supply-side capacity, their inflationary effects may be limited or even negligible. Supporting this view, Lartey (2016) finds that remittances have a minimal impact on the Philippine Consumer Price Index under an inflation-targeting regime.

4.2. Importance of inflation targeting and the rice tariffication policy

We now turn to the fixed effects quantile regression analysis of inflation, progressing from broad observations to more policy-specific insights. This section analyzes how rice and fuel prices affect overall inflation, particularly in the context of two key policy regimes: inflation targeting and rice tariffication. These policies have likely shaped inflation dynamics in distinct ways. Inflation targeting, for example, plays a pivotal role in managing the inflation process by anchoring expectations, which is the most important aim of central banks. McKnight, Mihailov, and Rangel (2020) point out its significance, noting that the difference between inflation expectations and the inflation target may be viewed as a measure of the central bank's overall credibility. Meanwhile, the impact of rice tariffication on inflation operates primarily through its ability to boost domestic rice supply via increased international trade.

We consider sub-sample periods related to inflation targeting and rice tariffication. We analyze sub-sample periods before and after the implementation of inflation targeting, covering August 1995 to December 2021 and January 2002 to April 2024, respectively. For the rice tariffication policy, we analyze two sub-sample periods, covering August 1995 to February 2019 and March 2019 to February 2024.

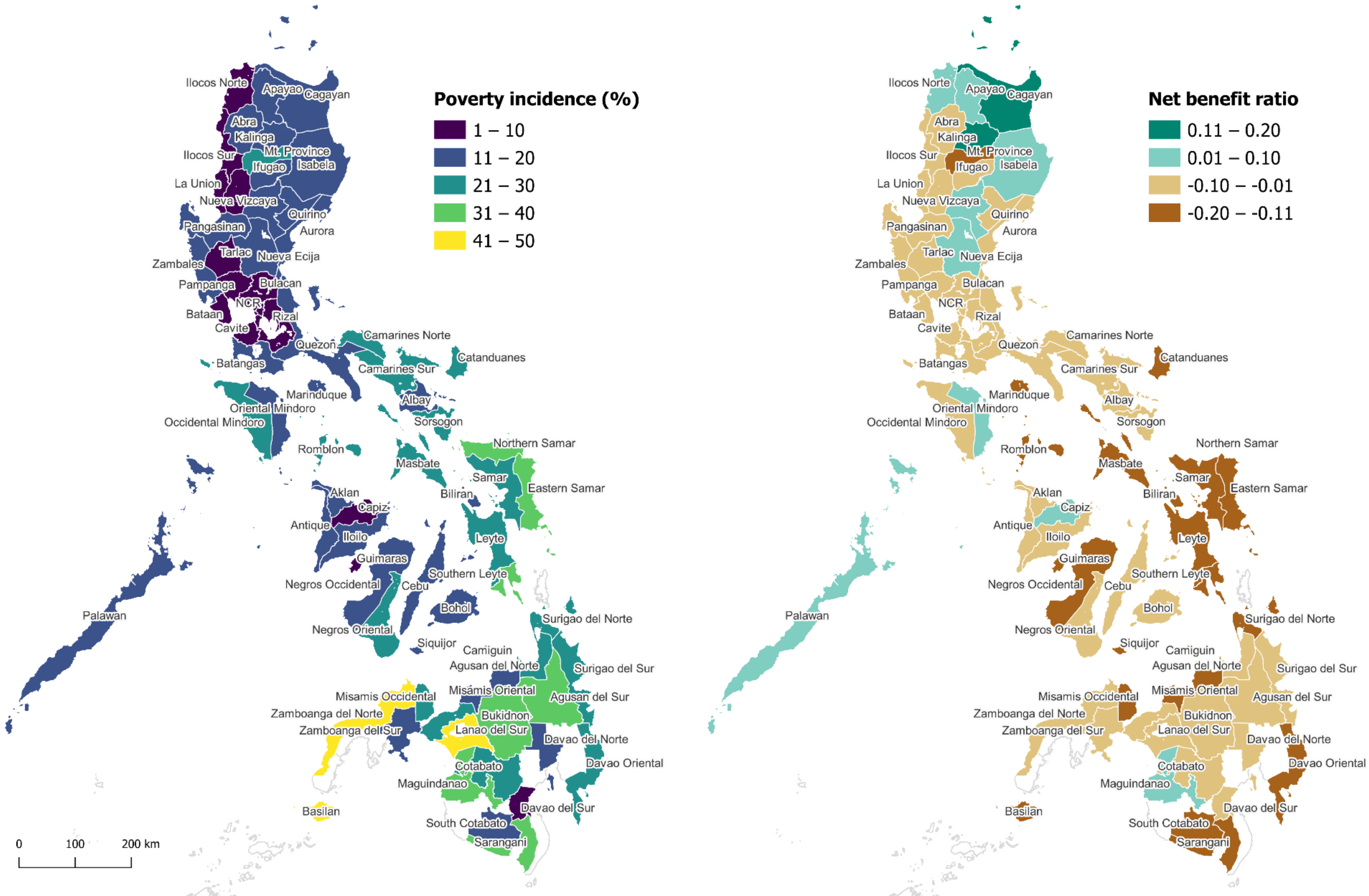
A comparison of the three panels in Figure 3 reveals the following key findings. First, the results consistently show that rice prices have a positive and significant effect on inflation across all quantiles, both before and after the implementation of inflation targeting and rice tariffication. However, the magnitude of this effect is smaller in the periods following these policy changes. Figures 3b and 3c further demonstrate that the influence of fuel prices is positive and significant at the lower quantiles prior to inflation targeting, and across all quantiles after rice tariffication. Second, the stronger impact of both rice and fuel prices on overall inflation at higher quantiles remains in the periods following the adoption of inflation targeting and rice tariffication.

4.3. Analysis of variation across provinces

We extend the analysis to a sub-sample of provinces to uncover variations in the impact of the rice tariffication policy for different poverty and rice self-sufficiency levels. Specifically, we estimate Eq. (3) for (a) low-, medium- and high-poverty provinces and (b) rice-surplus and -deficit provinces. This analysis could provide insights that may help shape addressing poverty and food insecurity.

To classify provinces by poverty level, we calculate the average national poverty incidence from the Family Income and Expenditure Survey (FIES) for 2015, 2018 and 2021. The FIES is a nationally representative survey of conducted by the PSA, covering about 41,000 households. Complete details of provincial poverty incidence are shown in Appendix Table A1. Figure 4 displays the average provincial poverty incidence over the 2015-2021 period. Provinces with poverty incidence of below 10%, 10-20% and above 20% were categorized as low, medium and high poverty, respectively.

Figure 4. Incidence of poverty and rice net benefit ratio by province.
Source: Analysis of data from the 2015-2021 Family Income and Expenditure Survey.



In classifying rice-surplus and -deficit provinces, we follow Balié, Minot, and Valera (2021) who apply Deaton (1989)'s NBR analysis using the 2015 FIES data to classify regions into net sellers or net buyers. We extend their analysis by calculating rice self-sufficiency levels across provinces based on average rice production share, rice consumption share, and the NBR. These indicators are calculated using Deaton (1989)'s formulation of the NBR:

$$\frac{CV}{Y} = (q - s)\hat{p} \tag{5}$$

where CV is the compensating variation measure of welfare, Y is household income or expenditure, q is the value of rice production as a share of expenditure, s is the share of total expenditure spent on rice, $\hat{p}$ is the proportional change in rice prices, and the term $(q - s)$ is the NBR. The NBR measures the short-term elasticity of household welfare in terms of the price of rice. A positive NBR indicates that a household is a net seller of rice, whereas a negative NBR suggests it is a net buyer.

Figure 4 also presents the NBR by province. Only 11 out of 74 provinces had a positive NBR, indicating they are surplus rice producers or net sellers. The top three NBRs were seen in the provinces of Kalinga (KAL) with 0.168, Cagayan (CAG) with 0.144, and Isabela (ISA) with 0.099. These findings align with expectations, as these provinces are considered the country's rice granaries.

In Figure 5, we present the quantile plots of the rice price inflation variable across the different categories of provinces. The plots present the coefficients at various quantiles, along with their respective confidence intervals. We observe that the rice price inflation variable still shows many instances of significance after the adoption of inflation targeting for the low- and high-poverty provinces. However, the impact of rice price inflation is much higher for high-poverty provinces than in the low-poverty group. Meanwhile, the impact of rice price inflation is lower in rice-deficit provinces than rice-surplus areas. Building on these findings, we provide additional insights into the idea that the prices of some goods are more salient than others when it comes to forming inflation expectations. To this end, we organized consumer inflation expectations data across provinces from the Consumer Expectations Survey (CES) conducted by the BSP's Department of Economic Statistics. The BSP conducts the CES on a quarterly basis with about 5,000 respondents from 52 provinces being asked about their demographic characteristics and expectations on inflation and other macroeconomic variables. We construct the following quarterly data on one-year ahead inflation expectations across households from 2014q2 to 2024q2 and took the average for each province:

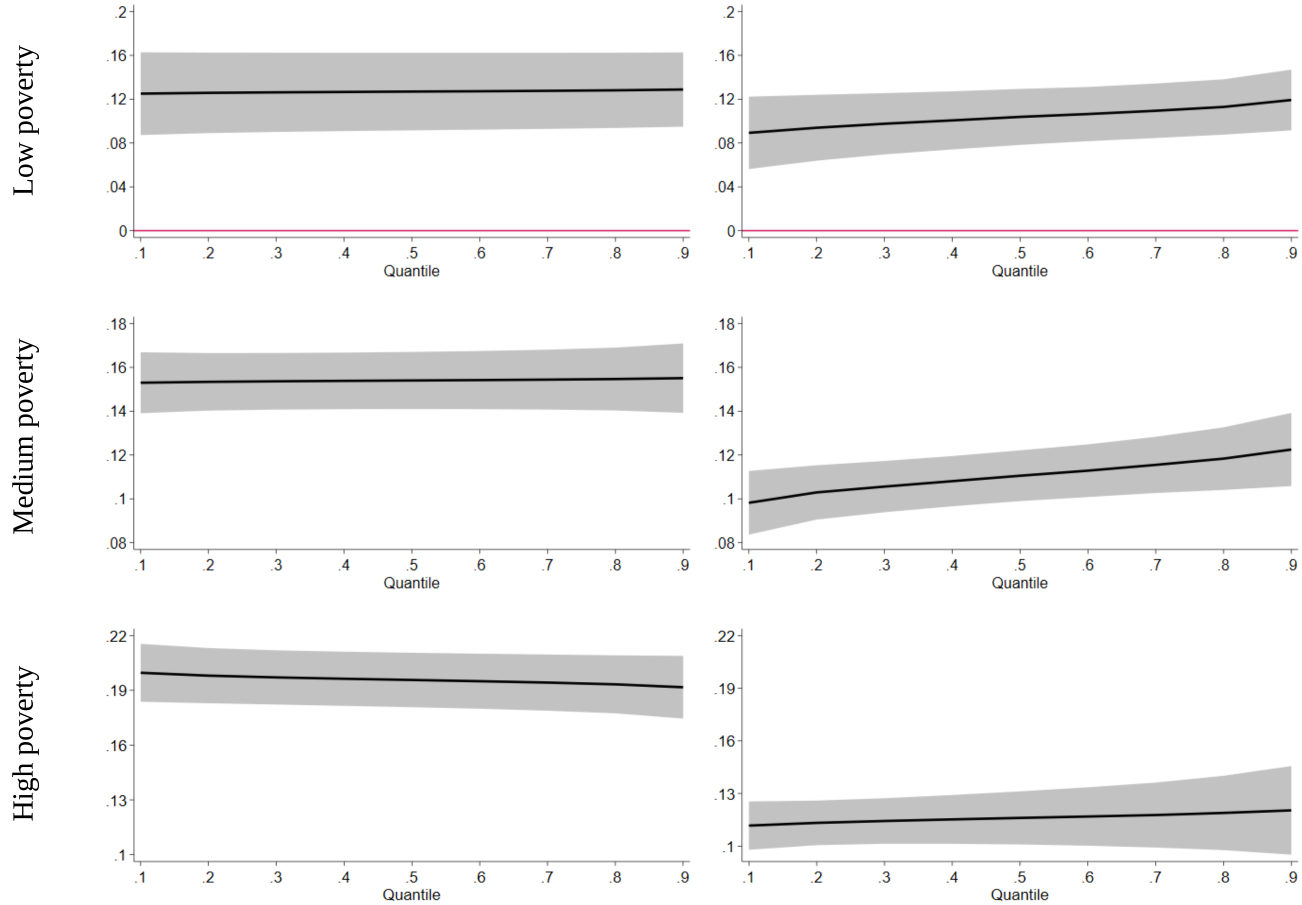
$$E_i \pi_{it}^e = \frac{1}{N_t} \sum_{i=1}^{N_t^*} \pi_t^e(i), \tag{6}$$

where $E_i \pi_{it}^e$ refers to the empirical cross-sectional means of individual inflation expectations in period *t*, $\pi_t^e(i)$ is the 12-month ahead inflation expectation of individual *i* who was surveyed in period *t*, and N_t is the total number of respondents in the relevant period. We obtain the cross-sectional means of inflation

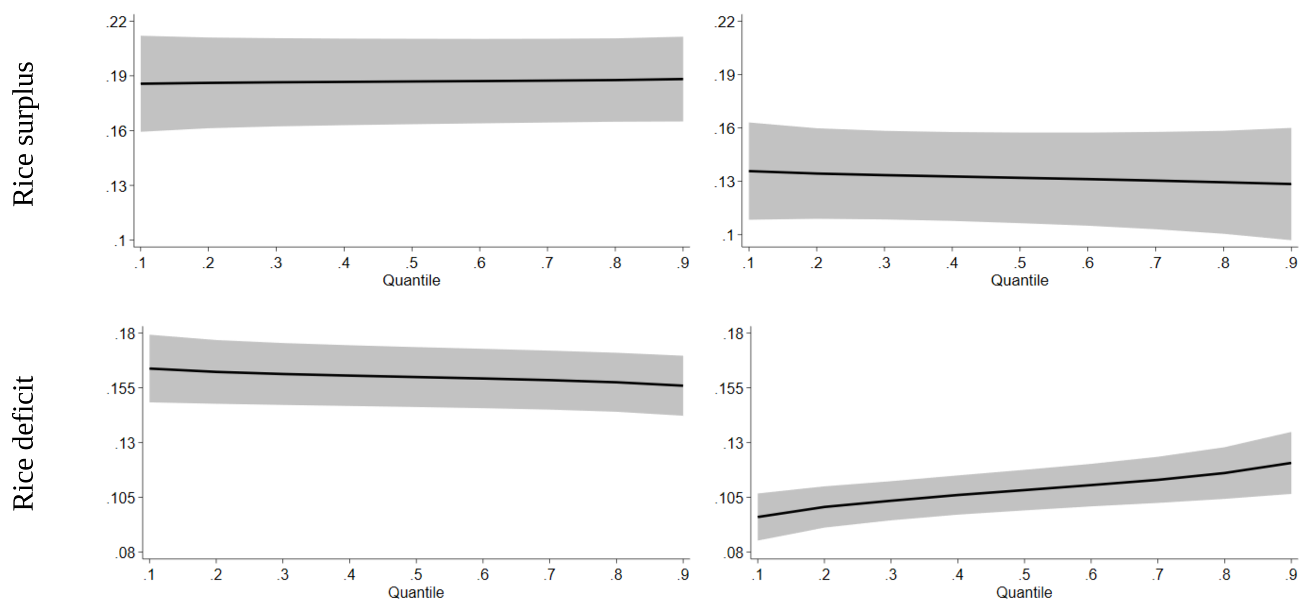
Figure 5. Fixed effects quantile regression results before and after rice tariffication.

Before rice tariffication	After rice tariffication

(a) Poverty levels



(b) Rice self-sufficiency levels



Note: Gray shaded area is the 95% confidence interval around the point estimates.

expectations for each of the 48 provinces that were included in the CES. We then match the average for each province with secondary provincial data on rice, diesel and gasoline prices.

Figure 6 shows the correlation between $E_i\pi_{it}^e$ and the prices of those three commodities for each province. The results show that inflation expectations are positively and significantly correlated with rice and fuel prices in most provinces. This finding supports existing studies that highlight the role of food and gasoline prices in determining household inflation expectations due to their salience (Berge 2018; Binder 2018; Coibion and Gorodnichenko 2015; Kikuchi and Nakazono 2023).

4.4. Do prices diverge across provinces?

The heterogeneous prices observed across our sample provinces do not necessarily imply that prices cannot diverge without limit across geographical areas. There could still be divergences in volatility in the short run even if long-run convergence is confirmed. Whether prices diverge across provinces remains an empirical question. We address this in the ensuing discussion using a suitable test for panel convergence comprising provincial-national inflation differential.

We implement the cross-sectionally augmented Im-Pesaran-Shin (CIPS) test proposed by Pesaran (2007), a widely used panel unit root test in the literature. The CIPS statistic is based on augmented Dickey–Fuller (ADF)-type regressions augmented with cross-section averages and performed separately for each series in the panel:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + \sum_{r=0}^{p_i} c_{ir}\Delta y_{i,t-r} + d_i\bar{y}_{t-1}\sum_{r=0}^{p_i} f_{ir}\Delta\bar{y}_{i,t-r} + \xi_{it} \tag{7}$$

where y_{it} is provincial-national inflation differential; Δ is the difference operator; $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$ is the cross-section average of y_{it}, which accounts for cross-sectional dependence; ξ_{it} is the effort term; $i = 1, \ldots, 74$ provinces; and $T = 1, \ldots, 342$ time observations. The CIPS test statistic is computed as:

$$CIPS = N^{-1}\sum_{i=1}^{N} t_i \tag{8}$$

where t_i is the ADF statistic based on the regression *t*-statistic for testing H_0: $b_i = 0$ in Eq. (7). The CIPS statistic tests the joint null hypothesis of a unit root against the alternative of at least one stationary series in the panel. For comparison, we also conducted the Im-Pesaran-Shin panel unit root test and the general diagnostic test for cross-sectional dependence (CD) in panels, known as the CD statistic (Pesaran 2021).

The results of the IPS, CD, and CIPS tests are reported in Table 4. The IPS test rejects the joint null hypothesis of a unit root, suggesting that the panel of provincial-national inflation differential can be treated as stationary. The CD and CIPS tests similarly reject the null hypothesis of joint non-stationarity in favor of the alternative. These findings support the convergence of prices across provinces. This finding corroborates our panel quantile regression estimates.

Figure 6. Province correlation: consumer inflation expectations and rice or fuel prices.
Source: Analysis of data from the 2014-2024 Consumer Expectations Survey.

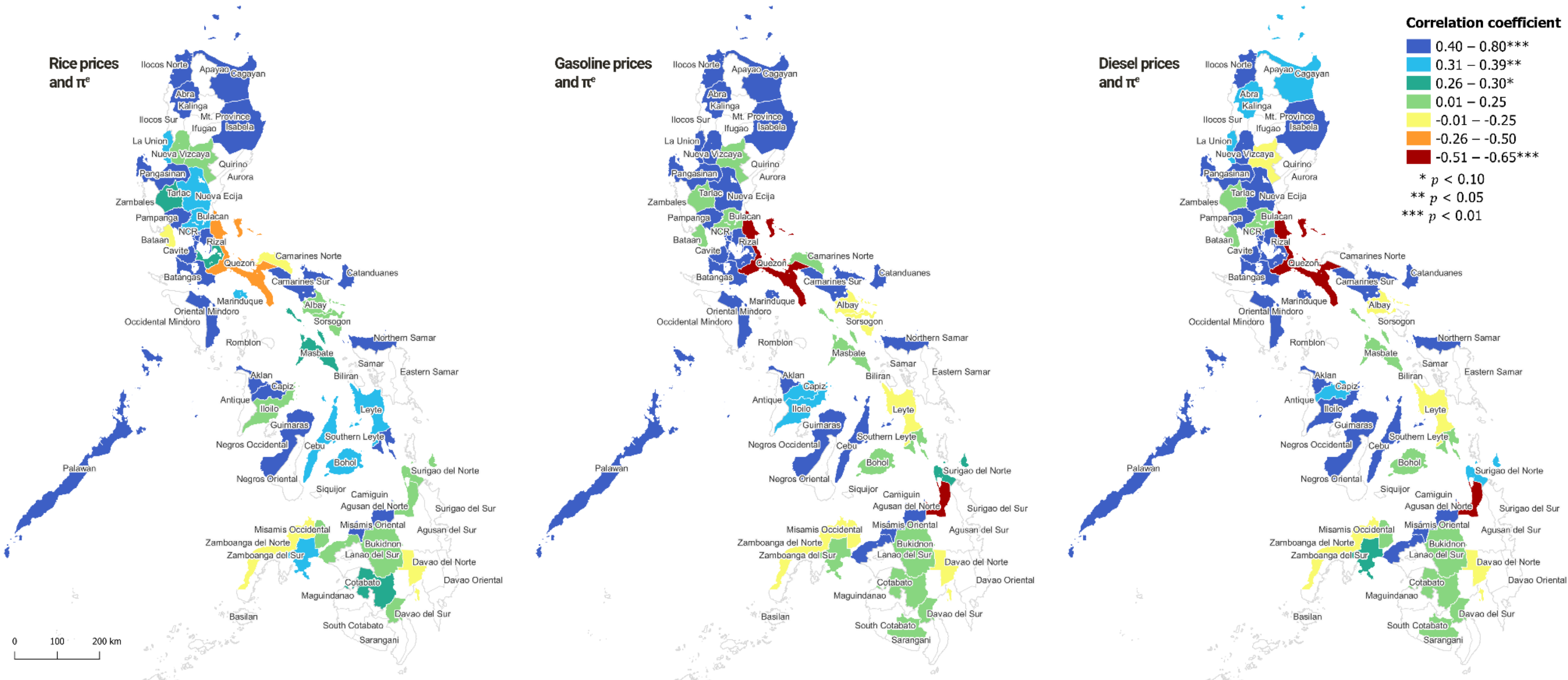


Table 4. Panel convergence test.

Panel unit root tests	Test statistic	*p*-value
IPS test (Im, Pesaran, and Shin 2003)	-31.47	(0.000)
CD test (Pesaran 2021)	23.25	(0.000)
CIPS test (Pesaran 2007)	-4.47	(0.000)

Notes: Lag lengths are determined by the Akaike information criterion. Figures in parentheses are *p*-values.

4.5. Further analyses and robustness

4.5.1. Unknown breaks in general inflation

Before and after comparisons of inflation targeting and rice tariffication can be influenced by other factors that change over time, particularly the share of household budgets going toward these items and the infrastructure for cross-province transportation and marketing of rice. This raises the question: Would dividing the sample at randomly selected years yield similar before or after results?

To answer the above question, we refine the analysis to identify structural changes by a specific year. We use the test for panels proposed by Ditzen, Karavias, and Weterlund (2021), which is based on an *F*-test and a null hypothesis of no breakpoints.

Table 5 reports the results for breaks in the general price. The breaks that we used in defining sub-sample periods are: (a) August 1996-July 2000, (b) September-April 2005, (c) June 2005-May 2009, (d) July 2009-May 2015, (e) July 2015-February 2020, and (f) April 2020-April 2024.

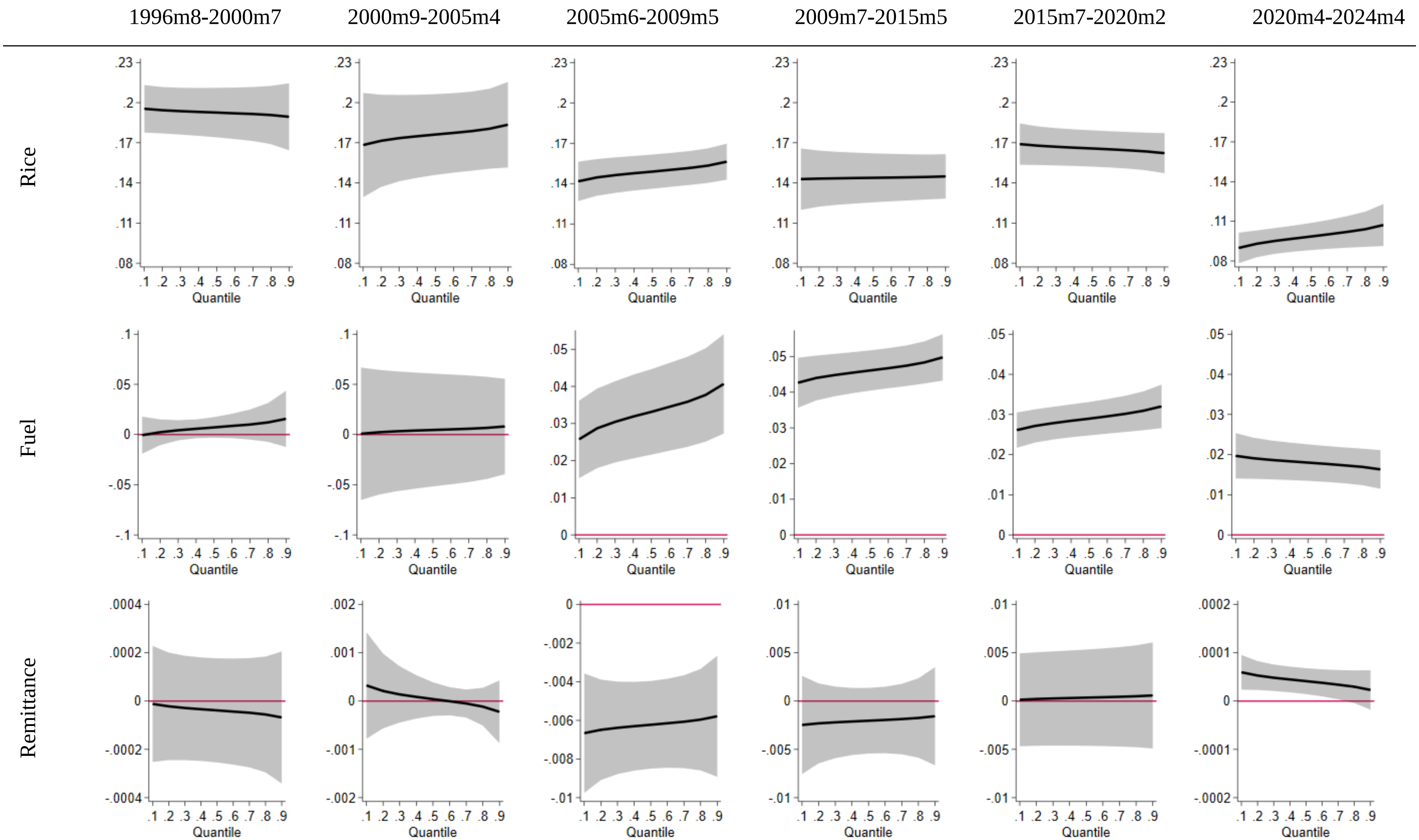
Table 5. Bai and Perron (2002) breakpoint dates.

		Critical values		
Breaks	Test statistic	1%	5%	10%
F(1|0)	6.21	12.29	8.58	7.04
F(2|1)	67.48	13.89	10.13	8.51
F(3|2)	98.5	14.80	11.14	9.41
F(4|3)	91.18	15.28	11.83	10.04
F(5|4)	93.47	15.76	12.25	10.58
Unknown breaks:	2000m8, 2005m5, 2009m6, 2015m6, 2020m3			

Notes: Test statistics and critical values are based on Ditzen, Karavias, and Weterlund (2021) sequential tests for multiple breaks at unknown breakpoints.

In Figure 7, the results are based on Eq. (3) and suggest that there is no significant change in either the direction or the magnitude of rice and fuel price effect on overall inflation after accounting for different sub-sample periods. In other words, the sub-sample results are largely consistent with the full sample estimates, with the nonlinear impact of rice and fuel prices on overall inflation mostly similar across periods.

Figure 7. Fixed effects quantile regression results for different sub-sample periods.



Note: Gray shaded area is the 95% confidence interval around the point estimates.

As for remittances, its significant positive impact on overall inflation is evident for April 2020-April 2024 sub-sample period. However, we also note that remittances have a zero slope inside the confidence interval across quantiles in most of the other sub-sample periods. Remittances shows a negative and significant effect on inflation across all quantiles for June 2005 to May 2009 sub-sample.

4.5.2. Alternative measures of rice surplus and deficit

Recall that our earlier calculation of the rice self-sufficiency levels across provinces relies on the NBR ratio in Eq. (5). One limitation of this measure is that the average rice production share and rice consumption share data are available for one period only based on the 2015 FIES. Thus, this approach does not consider the possibility that some rice deficit provinces in 2015 has transformed into rice surplus after a few years.

To resolve this issue, we create an indicative measure of rice self-sufficiency that offers another way of grouping rice surplus and deficit provinces using 2023 data. Following Clapp (2017), the self-sufficiency ratio *ssr* at the national level can be expressed with a simple mathematical model:

$$ssr = \frac{vp}{vp + m - x} \tag{9}$$

where v*p* denotes the domestic volume of milled rice production, *m* denotes imports and *x* denotes exports. An *ssr* of one indicates that the country is self-sufficient. An *ssr* lesser and greater than one indicates deficiency and surplus, respectively.

Analogous to Eq. (9), a provincial self-sufficiency indicator can be created based on the following procedures. First, we compute the per capita rice availability from the 2023 paddy production data, which were converted to milled rice equivalent using an appropriate milling recovery rate. The total milled rice equivalent in kilograms was divided by the 2023 projected population to calculate the per capita rice availability. Second, we estimate the provincial per capita rice utilization to have a basis for comparing the provincial per capita rice availability in creating the rice self-sufficiency index per province. The provincial per capita rice use is estimated by dividing the 2023 per capita rice utilization with 0.9 as food use comprises only 90% of the total rice use.

Accordingly, we calculate a provincial self-sufficiency index by dividing the per capita rice availability with the estimated per capita rice use. The resulting index was then used to identify a new set of deficit provinces with an *ssr* range of 0.00 – 0.99, and surplus provinces with an *ssr* of > 1.00.

The estimates generated based on these rice self-sufficiency measures confirm the results displayed in Figure 5. Results for the *ssr* indices by province and quantile regression are not reported here to conserve space, but these are available upon request.

4.5.3. Alternative model specifications and quarterly frequency

We consider three alternative model specifications in the next set of robustness tests. First, we address the reverse causality issue by using up to four lags of rice prices, fuel prices, remittances, and overall inflation. Results of the Dumitrescu-Hurlin (2012) panel causality test reported in Table 6 indicate that overall inflation Granger causes rice and fuel prices.

Table 6. Dumitrescu-Hurlin panel causality.

H_0	Lags	$\bar{Z}_{\text{stats}}$	*p*-value
Rice price inflation → Overall inflation	4	8.158	[0.000]
Overall inflation → Rice price inflation	4	2.253	[0.024]
Changes in remittances → Inflation	6	22.122	[0.000]
Overall inflation → Changes in remittances	5	9.064	[0.000]
Diesel price inflation → Overall inflation	6	6.855	[0.000]
Overall inflation → Diesel price inflation	4	21.965	[0.000]

Note: Optimal number of lags is determined by the Akaike Information Criterion.

Second, we include the Thailand 5% broken rice export prices to reduce concerns about omitted variables. Third, we check whether a model different from fixed effects quantile regression leads to the same conclusions about the influence of drivers of inflation. Specifically, we use the simultaneous quantile regression (SQR) model, which produces better estimates for multiple quantiles simultaneously compared to individually generated quantile functions (Liu and Wu 2011).

Figure 8 displays that the estimates obtained using these three specifications are similar to those obtained using the fixed effects quantile regression, confirming the validity of the baseline results. Our next robustness test deals with using monthly data by checking whether this differentiation is sensitive to quarterly data. Consistent with our findings using monthly data, Figure 8 shows that the inflationary impact of rice and fuel prices remains stronger when overall inflation is higher. The main conclusion is that the role of rice and fuel prices in driving inflation holds regardless of data frequency.

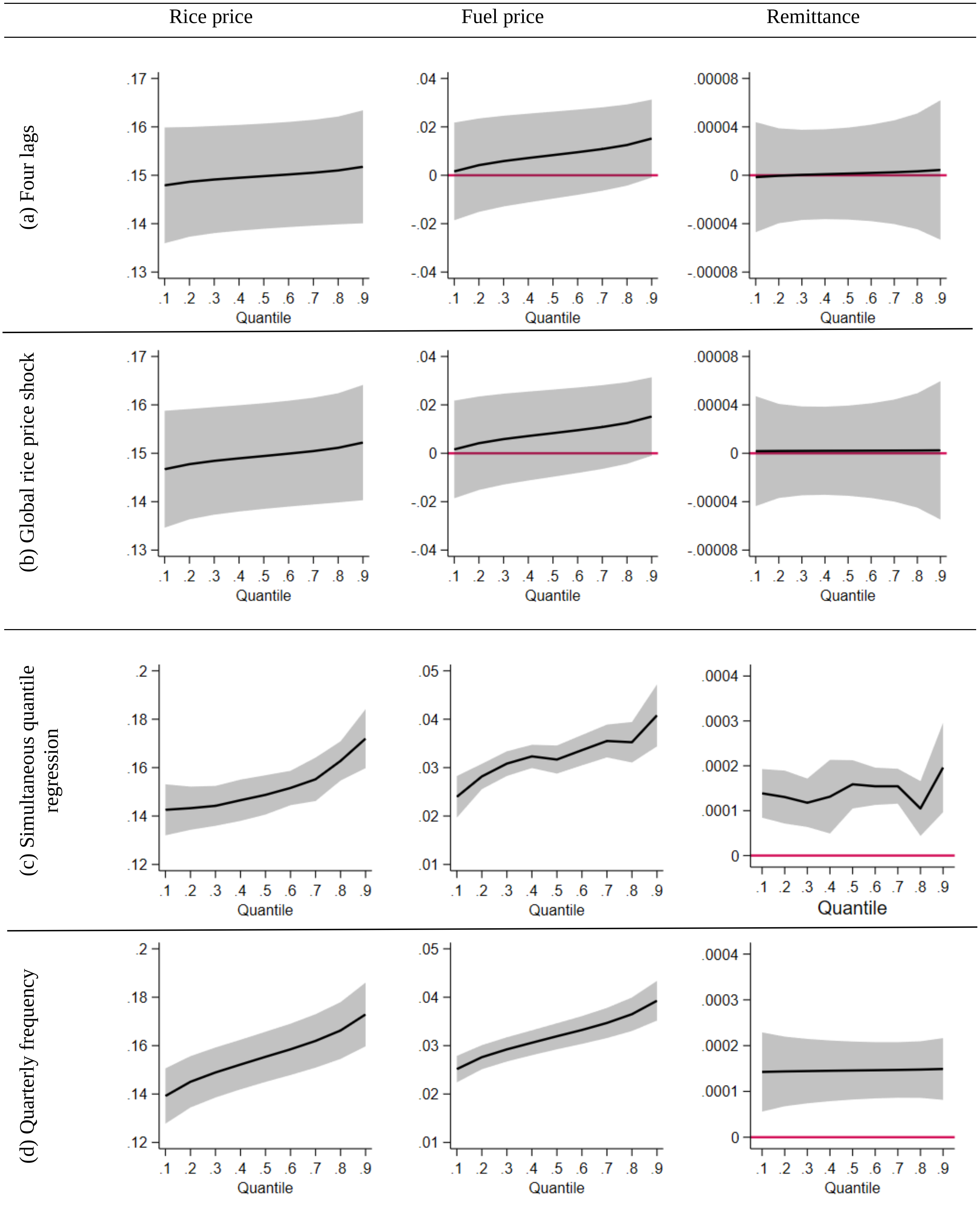
4.6. International comparison with Indonesia, India and Thailand

Figure 9 displays the results of the international comparison of the four Asian emerging markets. Despite differences in sample periods, the results remain consistent with the findings for the Philippines, suggesting a nonlinear impact of rice and fuel prices on overall inflation. The more substantial impact of rice or fuel prices is associated with more significant increases in overall inflation at the higher quantiles than in the lower ones. While the nonlinear impact of remittances remains, it induces more inflation in the lower quantiles than in the upper quantiles.

However, we do observe some differences in dynamics of the impact on inflation. Specifically, the significant positive impact of rice prices on inflation was noticeable for Indonesia and Thailand, but the nonlinear effect in Indonesia mimics that of the Philippines. The significant positive impact of rice prices on overall inflation in Thailand is rather similar across all quantiles. Rice prices in India show a significant positive impact on overall inflation only at the lower quantiles. The effect of fuel prices on overall inflation is positive and significant across all quantiles for all countries. However, the relatively higher inflationary effect of fuel prices is more pronounced in Indonesia and Thailand.

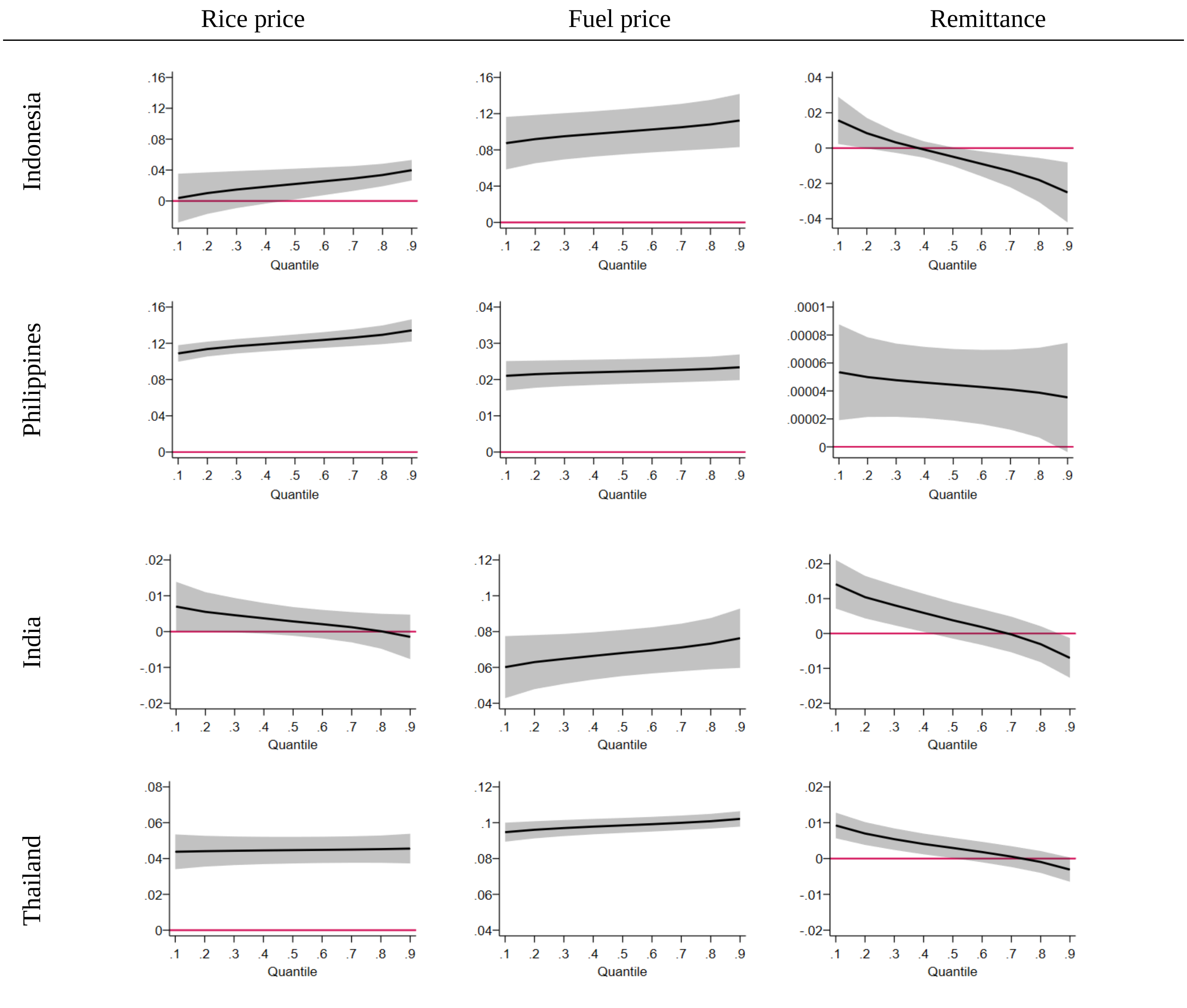
Turning to remittances, it shows a nonlinear impact on the Philippine overall inflation like the baseline results, with positive and significant impact being more pronounced in most quantiles. Finally, the remittance effect on overall inflation displays asymmetries for India, Indonesia, and Thailand, where such inflows positively impact inflation in the lower quantiles while negative in the upper quantiles.

Figure 8. Alternative model specifications and quarterly data frequency.



Note: Gray shaded area is the 95% confidence interval around the point estimates.

Figure 9. International comparison of fixed effects quantile regression results.



Note: Gray shaded area is the 95% confidence interval around the point estimates.

5. Conclusion

Understanding the sensitivity of inflation to commodity price fluctuations has been a key challenge faced by policymakers. Economists have usually tackled this question with inflation models using aggregate data that maybe uninformative due to the neglect of regional heterogeneity. This paper asked how our answers to this question become more revealing if we jointly account for price heterogeneity and state-dependent effects using monthly provincial panel dataset in the Philippines spanning nearly three decades. Using fixed effects quantile regression, our analysis shows a significant nonlinearity in the impact of rice and fuel prices on inflation across different inflation states. Notably, a pronounced positive and stronger impact of rice and fuel prices was observed during periods of higher inflation.

Moreover, we extend our investigation to analyze the consequences of inflation targeting, the rice tarrification policy and the association with poverty and rice self-sufficiency. Our evaluation shows the important role of those two policies in mitigating the impact effect of rice and fuel prices on overall inflation. In light of our findings, it also becomes apparent that rice tariffication has softened the impact of higher rice price inflation in in high-poverty and rice-deficit provinces. To gain an insightful angle through an international comparison, we have quantitatively verified the significant nonlinear impact of rice and fuel prices on geographically disaggregated inflation in most cases in Indonesia, Thailand, and India. Such comparative analysis also shows that remittances have a nonlinear influence on the Philippine inflation and asymmetric role in shaping inflation dynamics in the other Asian economies.

The findings have important implications for academic discourse and policy formulation. Our empirical analysis underscores the importance of considering the changing economic conditions and regional sensitivities to monetary and food policies when assessing the effects commodity prices and other determinants. From a policy perspective, it appears that inflation targeting regime has the potential to mitigate the inflationary impact of rice prices in times of high inflation when supported by the coordinated effort from the use of a supply-side reform like the rice tariffication policy. Integrating such policy tool with monetary measures could be beneficial elsewhere especially among net food-importing countries. Additionally, the asymmetric impact of remittances on inflation highlights the need for nuanced policy responses in economies with significant migrant populations.

Notwithstanding the above findings, there is scope for additional work. Our analysis sheds light on supply-side drivers of overall inflation differentials across provinces. Yet, our results are particularly silent regarding how demand-driven pressures and labor market interactions affect regional inflation dynamics. The authorities will benefit from a better understanding of the dynamics of such labor market narratives. Specifically, can provincial data be utilized to study more deeply the structural relationship between inflation and unemployment? This is particularly relevant for the case of the Philippines. Here, demand-driven inflationary periods or labor market reforms alter wage-price spirals. The novel course of actions is to pay attention to the approach proposed by Fitzgerald et al. (2024). They study whether the relationship between the US unemployment and future inflation is stable. They argue that using aggregate data to estimate this relationship is problematic as monetary policy systematically responds to economic conditions, which can obscure the true structural link between unemployment and inflation.

It also seems advisable to improve the measurement of provincial remittance flows. Future studies, for example, could explore alternative proxies or innovative data sources such as financial transaction records or mobile money transfers. The works by Kpodar and Imam (2024), and Ahmed, Mughal and Martínez-Zarzoso (2021) provide reference. Finally, there are many cereals that we did not consider in this study. Thus, an avenue for future research is to assess the relative impacts of prices of different cereals on inflation.

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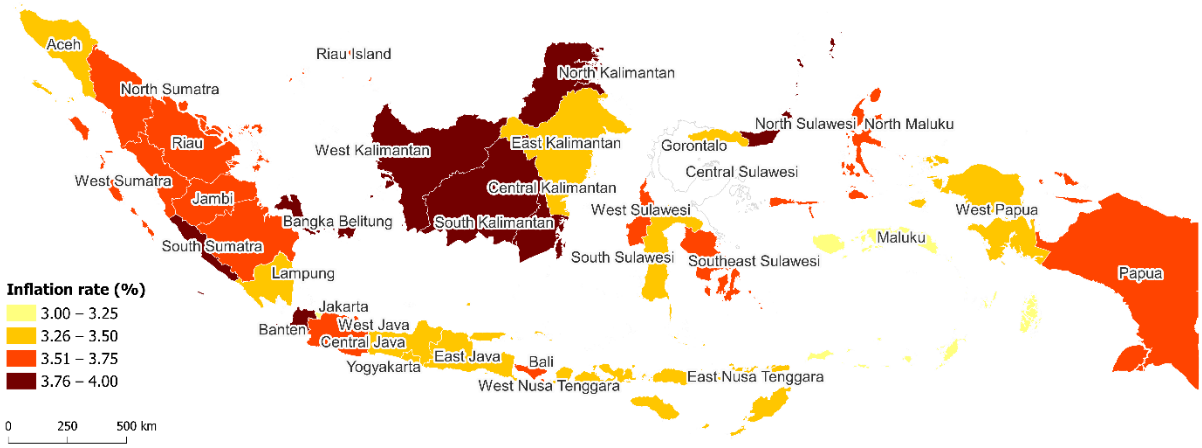
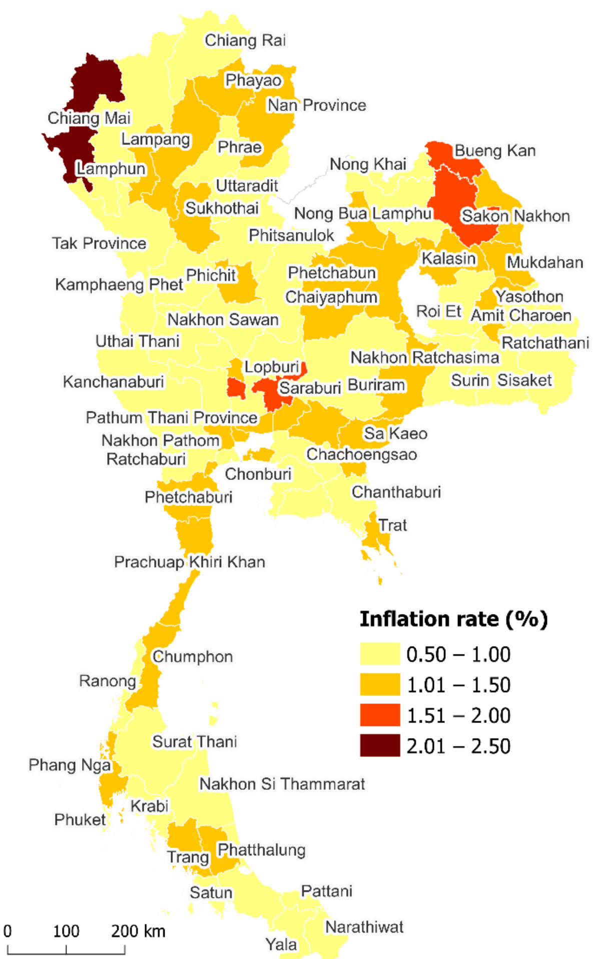
Appendix

Figure A1. Sub-national average overall inflation rate in Indonesia, Thailand and India, 2014-2024. Inflation data are from Badan Pusat Statistik, Bank of Thailand, and Dataful database.

(a) Indonesia



(b) Thailand



(c) India