Is there Price Distortion in the Philippine Rice Market: A Bayesian Discrete Wavelet Transform Analysis

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ABSTRACT

This study uses Bayesian Discrete Wavelet Transform (DWT) analysis to determine the existence of price distortions in the Philippine rice market. Using the world rice price as a benchmark, the study investigates residual fluctuations in rice prices from March 2023 to October 2024 at different frequency levels. The results show significant distortions at the approximation and detail coefficient levels, indicating inefficiencies influenced by market dynamics, policy interventions, and global trends. The Bayesian DWT approach detects localized price anomalies, thus enabling policymakers to examine market behavior and formulate stabilization policies in response to rice price fluctuations.

Keywords: rice price distortions, market inefficiencies, Wavelet Transform, Philippine rice market

INTRODUCTION

The rice market for food security, economic stability, and millions of livelihoods depend highly on the Philippines (Clarete et al., 2013). Analyzing price distortions whereby actual supply and demand by prices are not reflected has tremendous potential to guide proper policymakers' decisions that align with consumers and producers (Cororaton et al., 2009).

Rice is a staple for over 109 million Filipinos, accounting for a significant portion of daily caloric intake (Abeysekara & Rathnayake, 2024). The rice intake contributes to about 35% of the total dietary energy in the country (Angeles-Agdeppa & Custodio, 2020). Therefore, the rice market dynamics involve complex interactions between variables such as local production, importation, and government-related intervention (Lasco et al., 2008). A recent measure to curb the collusion price ceiling was lifted to bring proper prices during peak harvesting season. However, from the point of intervention from the government, it shows how distorted the prices are under price control (Soliva et al., 2024).

Price ceilings can upset the natural supply and demand balance. Suppliers may produce less or keep stock under wraps when the price is artificially low to avoid losing money. This causes a shortage (Price Caps Make Things Worse, n.d.). When there was a price ceiling on regular milled rice pegged at P41 per kilogram, the retailers began to hide the stocks or reclassify their lower-quality rice to stay below the cap (Soliva et al., 2024). Price distortions may result in low-quality products. In such circumstances, where incentives to keep quality are unavailable under price controls, consumers get low-quality products or pay more for premium quality (Mariano & Giesecke, 2014). This was when regular milled rice became scarce, and most of the time, the older or lower quality stocks were used instead (Mataia et al., 2020).

Several economists argue that such interference by the government through price ceilings leads to inefficiencies in resource allocation (Vogelsang, 2002). With price not reflecting real market situations, it creates misallocations of resources away from rice production and other sectors that are not similarly controlled. The misallocation has implications for the long-term sustainability of agriculture (Buzbee, 2007).

The Department of Agriculture recorded a downward trend in rice prices as reducing tariffs from 35% to 15% made imported rice more competitive (Office, 2024). Prices declined to a low of P45 per kilogram for well-milled rice in September 2024, showing that adjustments in the market can happen when distortions are reduced (DA-AFID, 2024). Impact on Consumers argued that price ceilings do not give a sense of security to the consumer but hurt producers. For example, in theory, consumers may benefit by having lower prices, but in practice, they must face shortages and lower quality. This double-edged sword shows that what is required is a true reflection of the market price through the price mechanism.

A necessity for food security, sustaining economic stability, and looking after consumer interest requires pinpointing the presence of any price distortions in the Philippine rice market. A price control decision requires policymakers to fully consider its implications toward fair pricing while ensuring they do not jeopardize its quality and availability. All parties from the rice supply chain need to constantly assess and analyze the different distortions to the markets under study.

This study promotes the United Nations Sustainable Development Goal (UNSDG) 2: Zero Hunger, mainly focusing on food security, improvement in market efficiency, and sustainable agricultural practices. Identifying price distortions in the Philippine rice market highlights the need for fair and stable pricing mechanisms that conform to global benchmarks to avoid economic inefficiencies and food access disparities. Such insights contribute to policy development aimed at reducing price volatility, enhancing market transparency, and securing the affordability and availability of rice, a staple food for millions, thus advancing progress toward eradicating hunger and achieving food security for all.

The aim of determining the presence of rice price distortions in the Philippine rice market compared to the world prices using Bayesian DWT is to identify and examine price behavior and volatility gaps. Bayesian DWT is an effective tool for decomposition into different frequency components. Therefore, short-term and long-term trends are analyzed with greater detail. This method unmasks underlying patterns and anomalies that may indicate market inefficiencies, external shocks, or policy impacts specific to the Philippines. Decomposing components into global price trends will inform whether the observed price movements in the Philippines are aligned with global market dynamics or whether significant deviations suggest price distortions. This analysis is essential for policymakers and stakeholders to implement measures that stabilize the rice market and ensure fair pricing for consumers and producers.

Theoretical Framework

The analysis of rice price distortions in the Philippines fundamentally stems from the nexus of agricultural economics (Swinnen, 2010), market structure (Pham, 2023), and government intervention (Anderson et al., 2013) theories. The theoretical framework begins with understanding price distortions, where the market prices diverge from their theoretical equilibrium price due to various internal and external factors (Ruiz-Buforn et al., 2019). In the Philippines, these distortions are incredibly complex (Bautista,1986) because of rice's strategic importance as a staple food and a critical agricultural commodity.

Neoclassical economic theory offers the main theoretical framework to analyze these price distortions. The basic model posits that rice prices should be determined by the interaction of supply and demand in an ideal market, with prices moving to balance market equilibrium (Bertrand, 1979). However, the Philippine rice market is far from this ideal, mainly because of massive government interventions, structural market inefficiencies, and unique agricultural characteristics (Chen et al., 2006). The theory of market failure is relevant in this case, given that various factors prevent the rice market from reaching perfect competitive conditions.

Agricultural policy theories provide some insight into the mechanisms of price distortions (Anderson (Ed.), 2010). The theory of agricultural price support is essential for understanding the dynamics in the Philippine rice market (Anderson, 2022). Government intervention through mechanisms such as price support programs, import quotas, and direct market intervention has significant deviations from the price level determined by the market (Anderson, 2010). From the food security perspective, theoretically, they are justified in protecting local farmers and maintaining social and economic stability (Anderson, 2022) but simultaneously introducing high price distortions.

Institutional economic theory is a critical perspective that stresses that formal and informal institutions in the market shape market behavior (Bocardo, 2003). In the Philippines, complex land ownership structures and traditional farming practices are reflected in intricate supply chain networks, leading to price distortions (Anderson & Martin, 2007). The theoretical model suggests that these institutional arrangements can create inefficiencies such that prices cannot adjust smoothly; thus, market imbalances are sustained (Anderson, 2015).

Trade economics theories further illuminate the phenomenon of price distortion (Anderson et al., 2013). Comparative advantage theory and models in international trade explain the global market dynamics and the interaction with local rice production and pricing (Anderson, 2013). Import policies, barriers to trade, and fluctuation in the global rice market add layers to price distortion. The Philippine rice market is then seen as a complex ecosystem wherein the international price trend interacts with domestic production capacities and government policies to determine the final prices in the market (Castonguay et al., 2016).

Development economics theories have valuable insights, especially concerning the involvement of agricultural markets in more holistic economic development (Mataia et al., 2020). The conceptual understanding recognizes rice as much more than a commodity and instead as a crucial constituent of national food security, rural livelihoods, and economic stability (Dawe, (Ed.) 2012). It has thus been understood that the distortion of prices is far more than an economic inefficiency; instead, it involves sociopolitical considerations (Tigno, 2012).

Behavioral economics provides another theoretical perspective. After all, market participants do not always act with perfect rationality. Risk perception, cultural practices, and historical experiences all shape market behaviors in ways that might not be fully captured by traditional economic models (Levinson & Peng, 2006). The theoretical approach helps explain why seemingly irrational pricing behaviors (Zhou et al., 2023) persist in the Philippine rice market.

Therefore, the theoretical underpinnings for deriving a rice price distortion remain complex and require an interdisciplinary approach (Ciarli & Ràfols, 2019) that integrates economic, institutional, and socio-political perspectives. These distortion factors require a framework from which to understand these distorting factors (Khatri et al., 2024), far-reaching in scope and complexity yet transcending simplistic supply-demand relationships to the intricate web connecting market structures, government policy, global trends, and local agricultural practices (Reddy & Rahut, 2023).

METHOD

An application of Bayesian Discrete Wavelet Transform (DWT) to rice price analysis in the Philippines (Retail Price. (n.d.)) and the world market (Rice - Monthly Price, (n.d.)) March 2023 to October 2024, is one powerful approach to identifying distortions in rice prices. It uses Bayesian inference to add precision to wavelet decompositions by including prior knowledge as well as uncertainty, making it a comprehensive multi-scale analysis (Wang & Li, 2009, December) of price dynamics. Wavelet analysis is highly beneficial as it captures the time and frequency components of the price data, providing insight into short-term fluctuations through detail coefficients and long-term trends through approximation coefficients (Johnstone & Silverman, 2005).

A comparison of the wavelet coefficients of rice prices in the Philippines to that of the global market was enabled by Bayesian DWT to detect anomalies or differences that indicate distortions (Divine & Godtliebsen, 2007) in the Philippine rice market. These distortions could be due to a variety of factors, including government policies (tariffs, import restrictions), market inefficiencies, or external shocks (supply chain disruptions, climate events) (Cheng et al., 2022). The low-frequency components highlight broader trends in price movements, while the high-frequency components reveal localized price volatility or transient distortions (Li et al., 2018).

The Bayesian framework ensures a statistically robust analysis, bringing in the uncertainty that inevitably emanates from price data measurements with errors, inferences of incomplete information, or pure market noise (Batondo et al., 2022). Using global price as a reference affords an objective baseline when measuring deviations specific to context over the Philippines. If the Philippine rice prices continue to exhibit systematic discrepancies on most scales of wavelet coefficients relative to world prices, then systemic distortions (Carpinelli et al., 2021) would be implied.

Ultimately, this method aids policymakers and market regulators by pinpointing periods and scales where distortions are most prominent, enabling targeted interventions to stabilize prices. Moreover, the integration of Bayesian DWT aligns with the broader goal of fostering transparency and fairness in agricultural markets, ensuring that local price dynamics are more closely aligned with global benchmarks.

In the context of the Bayesian Discrete Wavelet Transform (DWT) applied to rice price analysis, the mathematical representation of the wavelet transforms for a signal f(t), such as rice prices, is typically expressed as:

$$f(t) = \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} c_{j,k}, k\emptyset j, k(t) + \sum_{j=1}^{\infty} \sum_{k=-\infty}^{\infty} d_{j,k}\varphi_{j,k}(t),$$

Where:

$\emptyset_{j,k}(t)$ is the scaling function associated with approximation coefficients $\left(c_{j,k}\right)$, capturing low-frequency components or long-term trends in data.

$\varphi_{j,k}\ (t)$ is the wavelet function associated with the detail coefficients $(\,d_{j,k})$, capturing high-frequency components or short-term fluctuations.

j is the scale index, representing the resolution level of decomposition.

k is the translation index, representing the time location of the wavelet or scaling function.

$c_{j,k}$ and $d_{j,k}$ are the wavelet coefficients derived from the data, calculated as:

$$c_{j,k} = \int f(t)\emptyset_{j,k}\,(t)dt, d_{j,k} = \int f(t)\varphi_{j,k}(t)dt.$$

Bayesian DWT extends this standard DWT by incorporating prior distributions on the coefficients ($c_{j,k,}$ and $d_{j,k}$) to account for uncertainty in the observed rice price data. In this framework:

The observed price series is modeled probabilistically, often assuming a likelihood function $p\ (f(t) \mid \theta)$, where θrepresents the wavelet coefficient and other model parameters.

Prior distributions $p(\theta)$ are defined based on prior knowledge or assumptions about the smoothness or sparsity of the signal.

The posterior distribution of the coefficient is computed using Bayes' theorem:

$$p\big(\theta \ \mid f(t)\big) = \frac{p(f(t) \mid \theta)p(\theta)}{p(f(t))}$$

The Bayesian approach ensures that the resulting wavelet coefficients ($c_{j,k}$ and $d_{j,k}$) are just point estimates but are characterized by distributions, reflecting the uncertainty due to noise, sampling, or incomplete information in the price data.

Using the global rice price as the baseline ($f_{world}(t)$) and the Philippines rice price as the observed series ($f_{Philippines)}(t)$), the Bayesian DWT decomposes both price series into approximation and detail coefficients (Sun et al., 2015). These coefficients are then compared to determine the degree of alignment or distortion between the Philippines and global price trends. For instance, discrepancies in the detail coefficients may highlight short-term price shocks or market-specific anomalies (Liang et al., 2024) in the Philippine rice market. This equation framework allows for multi-scale analysis of price distortions, enabling targeted policy recommendations and deeper insights into drivers of price anomalies.

The Bayesian discrete wavelet transform provides significant advantages over the conventional method in analyzing price distortions in markets such as rice pricing. These advantages arise from the Bayesian approach, which can integrate prior knowledge, quantify uncertainty, and provide a flexible multi-scale analysis of time-series data (Ferreira & Lee, 2007), (Jiang et al., 2021).

This advantage Bayesian DWT holds in incorporating prior information about price fluctuations. The traditional DWT provides deterministic coefficients, but Bayesian DWT permits analysts to model expectations or historical knowledge about market behavior through prior distributions (Johnstone & Silverman, 2005). In an agricultural market like rice, where seasonal trends, external shocks, or government policies may affect prices, such a model helps increase the interpretability and relevance of the analysis (Li et al., 2018).

Bayesian DWT explicitly quantifies uncertainty in its outputs. Instead of producing single-point estimates for wavelet coefficients, it produces posterior distributions, capturing the variability and confidence associated with such estimates (Divine & Godtliebsen, 2007). This is important for identifying price distortions (Chaovalit et al., 2011) as policymakers and researchers assess the robustness of detected anomalies and avoid overreaction to noise or minor deviations in price trends.

Another significant benefit is that the multi-scale DWT enhances the Bayesian framework. Bayesian DWT decomposes price data into different frequency bands (Liu et al., 2022), allowing it to distinguish between short-term market fluctuations, such as supply chain disruptions or weather-related events, and long-term trends (Nabavi et al., 2024), such as shifts in global rice demand or trade policies. Traditional econometric models like regression or ARIMA may not be able to disentangle these components effectively in noisy or non-stationary data (Zhang et al., 2022). Bayesian DWT's flexibility allows researchers to analyze price behavior across scales while maintaining a probabilistic foundation.

Moreover, Bayesian DWT is more robust against noisy data than its non-Bayesian counterparts or more straightforward statistical methods (Wang & Li, 2009, December). In the case of rice pricing, data are often irregular due to measurement errors, missing entries, or volatility in reporting (Sun et al., 2015). The Bayesian approach incorporates prior distributions and evaluates likelihoods, which reduces the noise and produces smoother and more reliable decompositions of the price series (Wang & Li, 2009, December).

Bayesian DWT allows for comparing market behaviors, such as the alignment between Philippine rice prices and world prices. Bayesian DWT can, therefore, identify significant divergences (Yousaf et al., 2024) that are likely to be indicative of factual price distortions rather than random fluctuations (Safa et al., 2024) and may thus provide information about inefficiencies in markets, policy impacts, or structural barriers.

The Bayesian DWT is an extremely powerful toolkit for price distortion analysis that combines the benefits of wavelet-based multi-scale analysis with the probabilistic rigor of Bayesian methods. Its ability to incorporate prior knowledge, quantify uncertainty, and robustly handle complex time-series data makes it superior to many traditional techniques for understanding and addressing price anomalies in dynamic markets.

RESULT AND DISCUSSIONS

This study aims to analyze and compare the rice price trends in the Philippines with the global market over time from March 2023 up to October 2024 to determine the significant price difference and volatility between the local Philippine rice market and the broader international rice prices. This study targets factors that cause these price distortions in the Philippine rice market, such as the impact of government policies, supply chain inefficiencies, and structural market dynamics. The bottom line is to provide insight that can inform policymakers and stakeholders to improve the stability of the Philippine rice market regarding global price movements.

The Augmented Dickey-Fuller (ADF) test results in Table 1 are significant for the stationary analysis of logarithmically transformed rice price series of both the Philippines and the global markets. The test statistic

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for Philippines was -7.6457, and the world-level test statistic was -12.042, both of which were sufficiently more negative than the corresponding critical values at 1%, 5%, and 10% levels of significance, which were, for Philippines, -4.1378 and, globally, -4.2232; for 5%, -3.155 and, globally, -3.1894; and for 10%, -2.7145 for Philippines and, globally, -2.7298. The extremely low p-values (1.85E-11 for the Philippines, 2.23E-24 globally) strongly reject the null hypothesis of a unit root, indicating that the logarithmically transformed rice price series are stationary across both datasets. The test used seven lags for the Philippines and eight for the global series, with 12 and 11 observations used, respectively. This logarithmic transformation and subsequent ADF test were effective in addressing the initial nonstationary of the rice price series, providing a more robust statistical foundation for additional time series analysis by making sure that the data adheres to the fundamental assumption of stationarity required in many econometric modeling techniques.

Table I. Adf Test Result

Metric	Philippines	World
Test Statistic	-7.6457	-13.042
p-value	1.85E-11	2.23E-24
Lags Used	7	8
Number of Observations Used	12	11
Critical Values (1%)	-4.1378	-4.2232
Critical Values (5%)	-3.155	-3.1894
Critical Values (10%)	-2.7145	-2.7298

The descriptive statistics in Table 2 reveal significant characteristics of rice prices in the Philippines and globally, both in their central tendency and dispersion aspects. The mean price was 51.99 for the Philippines, well above the world mean of 33.49. This means that the domestic price market has a significant price premium.

Table II. Descriptive Statistics on the Rice Price in the Philippines and the World

	Philippines	World
Mean	51.99	33.49
Standard Error	1.05	0.83
Median	54.37	33.99
Standard Deviation	4.70	3.73
Sample Variance	22.13	13.91
Kurtosis	-1.29	-0.75
Skewness	-0.71	-0.53
Range	12.01	12.80
Minimum	44.43	26.09
Maximum	56.44	38.89

Further confirmation of this was from the median prices, given as 54.37 for the Philippines and 33.99 worldwide. A standard deviation of 4.70 for the Philippines might reflect more variability in price compared to a world's standard deviation of 3.73, perhaps due to more intricate market dynamics. Interestingly, both datasets reflect negative kurtosis: -1.29 for the Philippines and -0.75 globally. That would imply a flatter distribution than usual with fewer extreme values. The price distributions for both scenarios were skewed to the left since their negative skewnesses stand at -0.71 for the Philippines and -0.53 globally. It also implies that their range of prices is close to 12.01 for the Philippines and 12.80 globally. Meanwhile, for the Philippine market, the prices start from the minimum at 44.43 to the maximum at 56.44, and globally between 26.09 and 38.89. The statistics will draw unique pricing characteristics in the Philippine rice market, showing higher and more variable prices compared to the global context.

Figure 1 below illustrates rice price trends for the Philippines and the World from March 2023 to October 2024. Here, the Philippine rice prices are usually above the world average, and the gaps widen over time. More volatility is observed in the series for the Philippines, with generally more significant fluctuations. The

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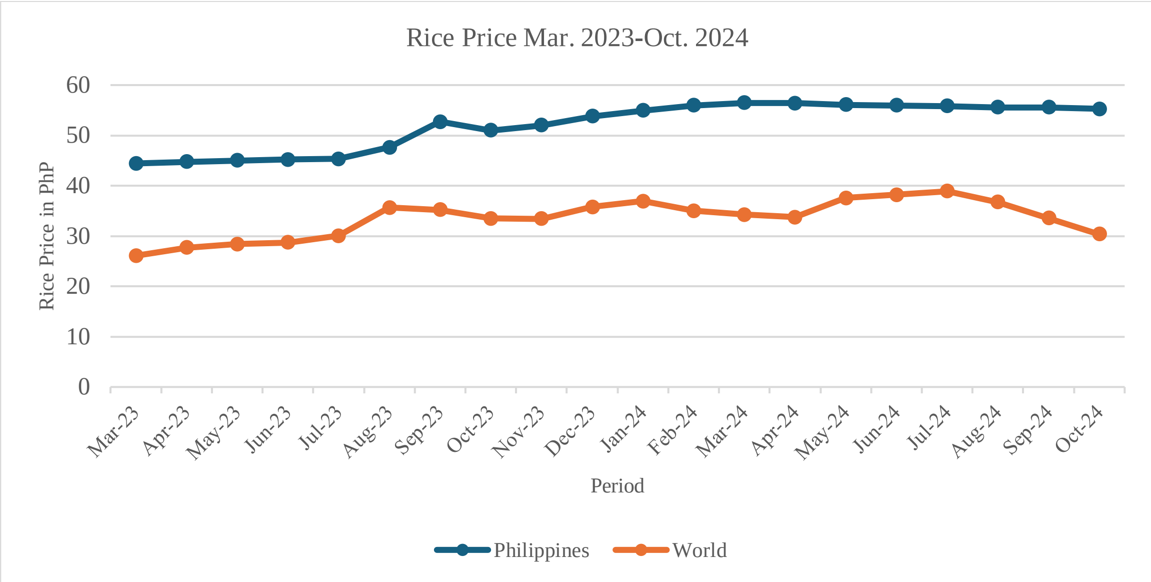
Philippines and the world rice price series show an upward trend during this period. The price of the Philippines' rice in the local market is ranging approximately P52 to P56 and in the international global approximately P26 to P39, which means the PH country rice market has immense price distortions compared to its market globally, probably because of state interventions, supply chain inadequacies, and systemic markets. These differences and the reasons behind them are to be understood by policymakers and stakeholders as ways of uplifting rice affordability and market stability in the Philippines.



From the analysis of the Bayesian Discrete Wavelet Transform coefficients of rice prices in the Philippines and the world market in Table 3, price distortions exist in the Philippine market relative to world trends. The approximation coefficients for the Philippines range from 3.303 to 3.490, while for the world, they range from 2.886 to 3.110. The consistently higher approximation coefficients in the Philippines suggest that the base price levels are generally higher than the global average. This difference may be structural, such as higher production costs, tariffs, or local market inefficiencies that cause price distortions in the Philippine market.

Table III. Bayesian Discrete Wavelet Transform Coefficients of Rice Prices

Approximation coefficients	Philippines	World
	3.303169	2.885535
	3.381783	3.050716
	3.46708	3.094475
	3.499775	3.109639
	3.489597	3.081541
Detail coefficients level-2	-0.00489	-0.02642
	-0.04743	-0.02112
	-0.02022	-0.01697
	0.003245	-0.04709
	0.002188	0.073118
Detail coefficients level-1	-0.00207	-0.0185
	-0.00143	-0.00333
	-0.0154	-0.05287
	0.010071	0.015197
	-0.01062	-0.02122
	-0.00565	0.016654
	0.000109	0.004609
	0.000548	-0.00549
	0.001599	0.017741
	0.001607	0.030379

The detail coefficients at level 2 capture medium-term fluctuations. For the Philippines, these coefficients are relatively small, ranging between -0.047 and 0.003, while for the world, they show more variability, ranging between -0.047 and 0.073. The minor variations in Philippine coefficients suggest a more rigid pricing structure, possibly influenced by government interventions, subsidies, or price controls that dampen medium-term price dynamics compared to the global market.

The detail coefficients at level 1 capture short-term fluctuations. In the Philippines, the coefficients vary between -0.015 and 0.0016, showing that the short-term price volatility is not that strong. On the other hand, global prices have a more significant range of fluctuation from -0.053 to 0.030, meaning that the global market is more responsive to immediate supply and demand shocks, exchange rate fluctuations, and international trade policies.

The findings reflect price dynamics with critical differences in Philippine rice prices, showing relatively higher baseline levels, approximation coefficients with very low fluctuation, and detail coefficients. This suggests a probable price distortion resulting from the various restrictions such as import, logistic inefficiencies, and competition in the local market. In comparison, the global price reveals high variability and represents a more accessible market under broader mechanisms of supply and demand.

It also means that the rigidity of prices and higher price levels in the Philippines suggest inefficiencies or intervention practices shielding the domestic market from worldwide trends, which become costlier for consumers. Adjusting these distortions will require reforms in agricultural policies, trade liberalization, and infrastructure development that might allow local prices to sync more closely with global standards.

Below is Figure 2, which contains three subplots that show the result of wavelet transform analysis: a comparison of data between the Philippines and the World. It is intended to analyze patterns or variances at several levels of decompositions using wavelet transforms. The Overlay Plot of Approximation Coefficients (Level-2) plot displays the approximation coefficients at Level-2, which are the low-frequency components of the data. The blue line, representing the Philippines, and the orange line, representing the World, both have an upward trend, indicating that the data for both regions have a similar overall pattern but differ slightly in their rate of increase over time. This is a long-term growth or structural change in both datasets.

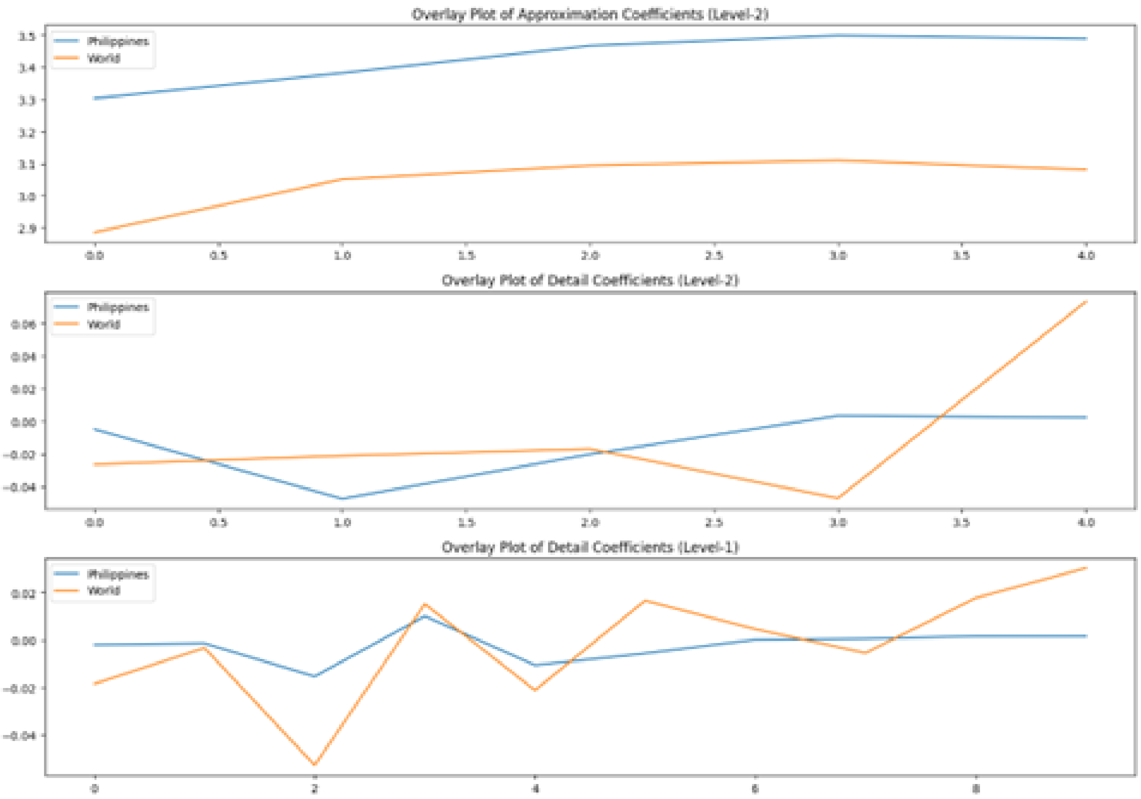


Figure 2. Wavelet transform analysis for the Philippines and World

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The second plot represents the detail coefficients at Level 2, which captures the high-frequency components of the data, such as fluctuations or short-term variations. Here, the blue line (Philippines) fluctuates within a narrower range and shows less volatility than the orange line (World), which experiences more pronounced fluctuations. This suggests that the data for the Philippines exhibits smoother transitions, whereas the global data may experience sudden changes or irregularities.

The Bottom Plot is the Overlapping Plot of the Detail Coefficients (Level-1) that represents the detail coefficients at Level-1, capturing even finer variations or noise in the data. Both lines show significant oscillations, but the orange line (World) has more pronounced peaks and valleys than the blue line (Philippines). This again suggests that the global dataset is more volatile in the short term than the Philippine dataset, which is more stable in behavior.

The wavelet decomposition in the figure does a great job of showing the differences between the Philippines and the World datasets at multiple levels. The patterns suggest that while both datasets share long-term trends (as seen in the approximation coefficients), the world data tends to be more volatile in the short term than in the Philippines, as suggested by the more fluctuating detail coefficients. This indicates underlying differences in the analyzed variables, such as economic, environmental, or social factors.

Figure 3 below depicts residuals of approximation and detail coefficients from a wavelet decomposition analysis, separately for the Philippines and global data. The top row presents residuals of approximation coefficients (Level-2), where both the Philippines and World trends exhibit a positive slope, with the World residuals displaying a slightly broader range. The second row shows detailed coefficients of residuals (Level-2) and depicts contrasting behaviors: the Philippines shows a stable yet downward fluctuation, while the World exhibits a steep rise toward the end. The bottom row focuses on detail coefficients (Level-1), where fluctuations are more pronounced, especially for the World data, with larger amplitude and variability than the Philippines. These plots collectively illustrate differences in decomposition residuals across scales and regions, highlighting nuanced variations at different levels of wavelet analysis.

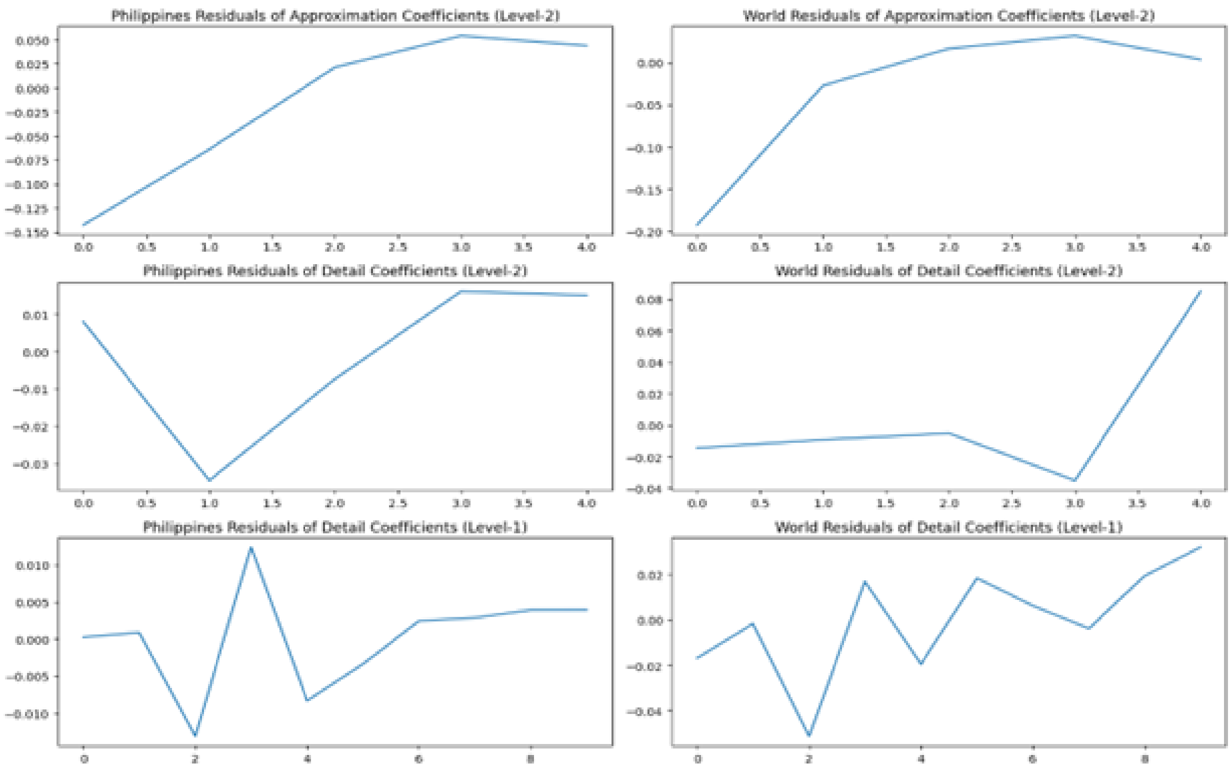

Figure 3. Residuals of approximation and detail coefficients from a wavelet decomposition analysis

The application of Bayesian Discrete Wavelet Transform to the analysis of price distortions in the Philippine rice market provides valuable insights that resonate with and extend the scope of economic theories on price formation and market efficiency. Specifically, Bayesian DWT allows researchers to detect discrepancies between Philippine rice prices and global prices across different time scales, offering a nuanced view of how price distortions manifest and persist.

From a neoclassical economic perspective, price distortions depart from equilibrium prices, often caused by market interventions, external shocks, or inefficiencies. The Bayesian DWT highlights these deviations by decomposing rice prices into various frequency components, thereby allowing the identification of short-term and long-term inconsistencies. For example, the decomposition captures short-term local price peaks not present in global patterns, indicating the effect of transitory supply chain shocks, hoarding, or weather-related shocks. Long-term divergences indicate structural issues such as trade barriers, protectionist policies, or persistent inefficiencies in the domestic rice market.

From the institutional and behavioral economics viewpoint, government interventions or market participants' expectations lead to price distortions. Quantifying the impacts of policies such as rice import tariffs, subsidies, or price ceilings is possible with prior information within the Bayesian framework. For instance, analysis deduces that while government price controls stabilize short-term price volatility, they also worsen long-term distortions by discouraging market competition or reducing incentives for domestic production.

Moreover, the Bayesian DWT highlights the importance of globalization and trade theories in explaining the local price dynamics. This analysis compares Philippine rice prices with global benchmarks to see if policies have effectively integrated or isolated the market from global trends. A large difference between the two indicates inefficient trade practices, limited access to the market, or reliance on domestic production, all contradicting the law of one price, which is the basis of international trade theory.

Bayesian DWT shares the nature of probabilism with market uncertainty and information asymmetry theories. The model explicitly captures price trends' uncertainties in this approach, enabling policymakers to distinguish genuine distortions from random noises. This characteristic is critical in the Philippine rice market, in which information asymmetry and speculative behavior magnify the distortions of prices. The Bayesian DWT model thus points to areas where distortions are caused by particular uncertainty, hence pointing to appropriate interventions at the sources of the distortions.

The inferences drawn from Bayesian DWT stress the complexity of price distortions in the Philippine rice market, which reflects the interaction between local policies, market behaviors, and global trends. This method verifies the existing economic theories and provides a robust multi-scale analytical framework for policymakers to design evidence-based solutions toward enhancing market efficiency and price stability.

CONCLUSION AND RECOMMENDATIONS

Using Bayesian DWT to analyze rice price distortions in the Philippines provides a robust and comprehensive approach to identifying and understanding market inefficiencies. With its ability to decompose the price signal into multiple time-frequency components and incorporate prior information, Bayesian DWT efficiently identifies short-term and long-term price deviations from global benchmarks that reflect domestic policy influences, market behaviors, and other external shocks. These insights are thus related to economic theories about distortions in the market, globalization, and information asymmetry, providing valuable evidence for policymakers to develop intervention plans. The quantification of uncertainty enhances the value of this method even further, so decisions could be made to address stabilizing rice prices or enhancing market efficiency in a Philippine context.

The study recommends that policymakers use the insights derived from the Bayesian Discrete Wavelet Transform to address the distortions in rice prices in the Philippines. Targeted market reforms are essential to help eliminate inefficiencies and promote price stability. These include transparency in the domestic supply chain, infrastructure improvement to reduce supply disruption, and re-evaluation of importation policies to align with the global market trend. In addition, the government should establish mechanisms for monitoring real-time price deviations using tools such as Bayesian DWT to respond to market shocks proactively. These measures will create a more efficient and resilient rice market, safeguarding consumer welfare and the sustainability of the agricultural sector.

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