UNIVERSITÀ DEGLI STUDI FIRENZE
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Working Papers - Economics

Vertical and Horizontal Price Transmission in the Rice Value Chain: the Case of Sri Lanka

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Working Paper N. 11/2025

DISEI, Università degli Studi di Firenze
Via delle Pandette 9, 50127 Firenze (Italia) www.disei.unifi.it

Vertical and horizontal price transmission in the rice value chain: the case of Sri Lanka

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Abstract

This study investigates the vertical and spatial integration of Sri Lankan rice market, using Hector Kobbekaduwa Agrarian Research Institute (HARTI) weekly price data covering the years 2008 to 2023. The analysis focuses on the implications of asymmetric price transmission (APT) on market efficiency and price dynamics within agricultural food supply chains, incorporating wholesale, retail, and farmgate price levels. Adopting a comprehensive methodological framework, the research includes stationarity tests, cointegration analysis, Granger causality assessments, Vector Error Correction Modell (VECM), and Nonlinear Autoregressive Distributed Lag (NARDL) approaches to explore nonlinear asymmetries in price adjustments. The findings reveal significant spatial and vertical integration across Sri Lankan rice markets and detect positive APT, although its magnitude varies when analysed by subperiods and agricultural season.

Keywords: agricultural prices, co-integration, vertical price transmission, Sri Lanka.

JEL codes: C32, Q10, Q13.

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Acronyms

ADF	Augmented Dickey Fuller Test
AIC	Akaike Information Criterion
APT	Asymmetric Price Transmission
ECM	Error Correction Model
ECT	Error Correction Term
HARTI	Hector Kobbekaduwa Agrarian Research Institute
NARDL	Nonlinear Autoregressive Distributed Lags Model
PMB	Paddy Marketing Board
RS.	Sri Lankan Rupees
VECM	Vector Error Correction Model

Acknowledgements

This research would not have been possible without the close collaboration with the Hector Kobbekaduwa Agrarian Research Institute (HARTI), which provided the dataset and hosted me as a visiting researcher for three months in Colombo. I particularly acknowledge the pivotal role played by Dr. Samantha N.P.G., Additional Director and Head of Research at the institute. His contributions were crucial in connecting me with local researchers and facilitating the circulation of my work, enabling me to receive valuable feedbacks. Furthermore, I would like to emphasize the pivotal role of Professor Donato Romano, whose close supervision was instrumental to this research, and Dr. Antonio Scognamillo, who facilitated valuable connections in Sri Lanka and provided me with the opportunity to engage in fieldwork, an experience that profoundly transformed my perspective as a researcher.

1. Introduction

Rice is the single most important crop in Sri Lanka, accounting for 34% of the total cultivated area (FAO and WFP, 2023). Paddy production involves approximately 1.8 million family farmers, with nearly 30% of the population directly or indirectly engaged in the paddy/rice industry. Most paddy farmers (over 75%) are smallholders, cultivating less than one hectare of land, while only about 3% manage areas larger than two hectares (Perera et al., 2021). Rice is also the typical staple food for Sri Lankans, with a per capita consumption of approximately 100 kg per year, accounting for 13% of the average household food expenditure (Central Bank of Sri Lanka, 2020). It provides 42% of the total calorie intake and 34% of the total protein requirement for the average individual, holding the highest nutritional contribution from a single food commodity in the Sri Lankan diet. Historical time series data on rice consumption indicate that rice has long been the primary staple food for Sri Lankans, with no sign of a shift towards high-value protein products (Gedara et al., 2015). This enduring preference for rice underscores its pivotal role in the Sri Lankan diet and economy.

The price of rice in Sri Lanka, similar to that of many other crops, has recently experienced a severe shock due to a combination of internal policies and external global factors. In September 2022 Sri Lanka faced a food inflation of 94.9%, reaching its historical maximum (Central Bank of Sri Lanka, 2022). By November 2022, Sri Lanka still ranked 6th globally in food inflation with a rate of 86.5% (World Bank, 2022). This soaring inflation was due to disruptions in the supply chains caused by the COVID-19 pandemic (Hassen and El Bili, 2022) and the Russia-Ukraine war which significantly impacted commodity markets, particularly food and energy, thereby affecting global trade, production, and consumption patterns. Additionally, on May 06, 2021, Imports & Exports (Control) Regulation No 07 of 2021 was issued, banning the import of chemical fertilizers, pesticides & herbicides. This measure was aimed to promote organic production and consumption and to reduce government expenditure, as imported chemical fertilizers were heavily subsidized to boost domestic rice production. However, the availability of organic fertilizers was insufficient to meet crop requirements, leading farmers to demand the return to the previous regime of chemical fertilizer imports. After months of protests, the government withdrew the ban on November 30, 2021 (Weerahewa and Dayananda, 2023). However, farmers struggled to access supplies as the global price of fertilizer has been increasing since September 2021, eventually soaring after the invasion of Ukraine (Hebebrand et al., 2023). The underuse of chemical fertilizers led to a significant reduction in rice crop yields during the *Maha*[2] 2021/2022 season.

Given its crucial role in Sri Lankan economy, understanding how the paddy rice markets reacted to the recent price shocks is crucial to learn lessons to ensure national food security and employment. In doing this, examining market integration is pivotal. Well-integrated markets are fundamental for efficient value chains, as they facilitate accurate price transmission and the effective movement of commodities. In perfectly integrated markets, price movements are fully and instantaneously transmitted throughout the entire supply chain, ensuring optimal market

[2] *Maha* (October - March) is the primary agricultural growing season, while *Yala* (April - September) is the secondary growing season.

functioning. Conversely, poorly integrated markets may transmit inaccurate price signals, leading to inefficiencies within the supply chain (Goodwin and Schroeder, 1991).

Market integration can be categorized into two types: horizontal market integration and vertical market integration. Horizontal market integration occurs when the price of a commodity in one market responds to changes in the price of the same product in other markets. Vertical market integration, on the other hand, refers to the integration of the price of the same product at different levels of the value chain, such as farm price, wholesale price, and retail price (Paul and Karak, 2022). This paper aims to study both spatial and vertical integration in the Sri Lankan rice sector. First, we will assess the spatial integration among geographically separated markets in Sri Lanka and analyse the price transmission dynamics using wholesale prices. Furthermore, the paper will investigate the vertical integration among wholesale, retail, and farmgate prices in the rice value chain. After examining price transmission and adjustment to shocks, we will assess whether the price transmission is symmetric or asymmetric.

Asymmetric Price Transmission (APT) refers to the phenomenon where a market responds differently to price increases compared to price decreases. For instance, output prices might react immediately to input price increases but more slowly to input price decreases. APT is a major cause of marketing inefficiency. In the long run, APT hinders the efficient movement of price signals between markets, influencing farmers' decisions. It also prevents certain groups from receiving the full benefits of price changes while granting undue advantages to others, leading to distributional impacts and welfare transfers.

According to Meyer and Von Cramon-Taubadel (2004), asymmetry in price transmission can be classified according to three criteria. The first criterion concerns whether the asymmetry is in the speed or the magnitude of price transmission. APT with respect to speed results in a temporary transfer of welfare, the size of which depends on the transmission period and transaction volume. Asymmetry in magnitude leads to a permanent transfer of welfare, though its size depends on transaction volumes and price changes. Asymmetry in both speed and magnitude results in a combination of temporary and permanent welfare transfers. The second criterion, as outlined by Peltzman (2000), classifies APT as either positive or negative. Positive asymmetry occurs when the output price reacts more fully or rapidly to an increase in the input price than to a decrease. Conversely, negative asymmetry denotes a situation where the output price reacts more fully or rapidly to a decrease in the input price than to an increase. The third criterion classifies APT based on whether it affects vertical or spatial price transmission.

The most frequently cited reason for APT is the presence of market power. Some agents may act as price makers while others act as price takers along the supply chain, depending on the industry's degree of concentration. For example, input price increases in an industry may be passed on to consumers, while input price decreases might be captured in the industry's mark-ups (Conforti, 2004). Therefore, the market structure plays a pivotal role in determining whether the price transmission process is symmetric or asymmetric. This is particularly salient to the rice sector in Sri Lanka, because there are some priors of concentration within the rice milling sector. According to the literature, there is a widely held belief in Sri Lanka that large-scale millers, with their extensive resources and political connections, manipulate the rice market (Adhikarinayaka, 2005; Rupasena, 2002). These large-scale millers possess advanced milling technology, established brand names, and eventually economic and political power enabling them to engage in lobbying and enforcing entry restrictions, thereby disadvantaging small-scale millers.

Wijesooriya and Kuruppu (2022) investigate the market power of the rice milling industry in Sri Lanka, focusing on the Polonnaruwa district where the majority of paddy milling occurs in the country. The paddy/rice value chain in the Polonnaruwa district mainly consists of a large number of small-scale paddy farmers, a few paddy collectors, very few large-scale rice millers, a few medium-scale rice millers, many small-scale rice millers, rice wholesalers in main cities, and a large number of retailers spread across the country. They conclude that nearly half of the rice production in the Polonnaruwa district is governed by the four largest millers, indicating a significant market power.

Mufeeth et al. (2022), adopting the New Empirical Industrial Organization (NEIO) approach, estimate the presence and factors affecting the market power of the rice milling industry in Sri Lanka. Their findings suggest that the market structure of the rice milling industry was neither perfectly competitive nor a monopoly, confirming the presence of oligopolistic market power in the Sri Lankan rice milling industry between 1982 and 2019.

Given this market structure and the importance of rice production and consumption in Sri Lanka, studying the price efficiency of the rice sector is paramount. Understanding how rice prices transmit in the market is essential for guiding policymakers in formulating policies that ensure the efficient movement of rice prices, aiming at having a more competitive rice market. Additionally, providing evidence of Asymmetric Price Transmission (APT) is crucial for understanding which actors in the rice value chain bear the cost of market inefficiencies. The novelty of this study lies in its ability to address three critical gaps in the existing literature: first, by incorporating farmgate prices into the analysis of Asymmetric Price Transmission (APT) for rice in Sri Lanka, the study captures a more holistic view of price dynamics at the production level. Second, it provides a timely examination of price transmission following the 2022 price shock, offering insights into how recent economic disruptions have impacted market behaviour. Finally, the study integrates both spatial and vertical price transmission, presenting a nuanced understanding of how prices move through different regions and supply chain levels within the Sri Lankan rice market. These contributions have far-reaching implications for policy, particularly in crafting targeted interventions to reduce the negative effects of price shocks, enhance market integration, and promote equitable price transmission, ensuring that both producers and consumers benefit from market reforms.

The paper is organized as follows: the second section reviews the theoretical literature on APT and provides empirical evidence of its presence in rice markets. The third section describes the context, data, and methods. The fourth section discusses the results. The last section concludes.

2. Literature review

Meyer and Von-Cramon-Taubadel (2004) state that most publications on Asymmetric Price Transmission (APT) attribute its occurrence to non-competitive market structures. In agricultural markets, farmers at the beginning and consumers at the end of the marketing chain often suspect that imperfect competition in processing and retailing enables intermediaries to exploit market power. It is generally expected that this results in positive APT, where margin-squeezing increases in input prices (or decreases in output prices) are transmitted faster and/or more completely than the corresponding margin-stretching price changes (Meyer and Von-Cramon-Taubadel, 2004).

Bakucs et al. (2014) investigate the causes of vertical APT in the agro-food chain by conducting a meta-analysis of existing studies. They conclude that asymmetric price transmission in farm-retail relationships is more likely to occur in sectors or countries with fragmented farm structures, higher governmental support, and more restrictive regulations on price controls in the retail sector.

Rose and Paparas (2023) review alternative explanations for APT as reported in the literature, such as inventory management and the perishability of agricultural goods. Inventory management systems, such as first-in-first-out (FIFO), tend to create time lags because retailers do not adjust product prices immediately. Instead, they wait for the old stock, purchased at the original price, to be depleted to avoid profit margin loss. The perishability of goods also affects price transmission, contributing to short-term market price fluctuations. The literature suggests that retailers may be cautious about farmgate price increases, fearing that such increases would deter customers, leading to unsold produce that would spoil. This mechanism is exacerbated when storage facilities are inadequate.

Alam et al. (2016) use time series estimation methods to test asymmetric price transmission in the vertical chain of Bangladesh rice markets. Their results show that wholesale and retail prices are integrated in the long run, with a unidirectional causality from wholesale price to retail price, consistent with the mark-up pricing model. Prices are discovered at the wholesale level and influence retail price adjustments. Furthermore, they find that retailers respond more quickly to decreases in their margins than to increases, indicating systemic pricing inefficiencies within Bangladeshi rice markets. This affects both producers' and consumers' welfare, as farmers are unable to reap the benefits of price increases at the retail level, while consumers cannot take advantage of price falls at the production level. This indicates market power at the wholesale level along the value chain. Furthermore, the presence of shocks or threshold effects in price transmission underscores the urgency of policy interventions in the domestic rice market to maximize welfare for both producers and consumers.

Deb et al. (2020) also investigate market integration and price transmission along the vertical supply chain of rice in Bangladesh. They found that negative deviations are more persistent than positive deviations in upstream market pairs (i.e., farm-wholesale), causing farmers to suffer from price decreases for a longer period. Conversely, in downstream market pairs (i.e., wholesale-retail), positive deviations from long-run equilibria persist longer than negative deviations, harming impacting end consumers. This finding aligns with industrial organization theory and supports the so-called ‘rocket and feather’[3] hypothesis, where prices rise like a rocket but fall like a feather.

Gedara et al. (2015) analyse asymmetry in price transmission between wholesale and retail rice markets in Sri Lanka. They find that the wholesale and retail rice markets in the country are integrated, with price changes moving from the wholesale to the retail market. However, the price transmission process is asymmetric. Specifically, price increases at the wholesale market transmit immediately to the retail market, while price decreases transmit more slowly. Accounting for structural breaks, they found that the price transmission process is asymmetric only during periods of price surges, suggesting market inefficiency during these periods. Consequently, consumers are temporarily denied price reductions in the wholesale market.

Harshana and Ratnasiri (2023) evaluate APT in terms of magnitude and speed between the wholesale and retail levels of the Sri Lankan fruit and vegetable markets using monthly data on wholesale and retail prices of 12 vegetable and three fruit varieties from 2005 to 2019. They find evidence of APT, with positive shocks in wholesale prices of fruits and vegetables transmitting more significantly to retail levels compared to negative shocks, indicating that consumers are more likely to experience price increases at the retail level following positive wholesale price shocks.

Jayasinghe-Mudalige (2006) examines the impact of prices originating in the Central Rice Market (i.e., Colombo) on price formation in geographically dispersed regional rice markets in Sri Lanka (i.e., Anuradhapura, Kandy, Kurunegala, Nuwara-Eliya, and Polonnaruwa) using monthly retail prices from January 1996 to December 2003. The analysis suggests that prices in these markets are highly integrated both in the short-run and long-run perspectives.

Rifana and Abayasekara (2023) study regional integration and price transmission among geographically separated rice markets in Sri Lanka. They use weekly wholesale prices of rice from 2000 to 2019 for Colombo's Pettah market (central market) and regional markets in Gampaha, Kandy, Kurunegala, Puttalam, Dambulla, Thambuththegama, and Dehiattakandiya. Johansen co-integration tests indicate significant long-run integration between the central and regional markets. The Vector Error Correction Model reveals integration in both short and long runs, with disequilibrium corrected within seven to twenty-five weeks. The Granger causality test indicates bidirectional causality between Pettah and regional markets, suggesting efficient price transmission processes.

Alam et al. (2022) investigate spatial market integration among five major Bangladesh markets from January 1999 to December 2021. Using a threshold cointegration approach to account for transaction costs, they find that large price deviations from long-run equilibrium are corrected within two three months. Their results highlight the need for policies aimed at reducing transaction costs to enhance pricing efficiency in Bangladesh rice markets.

[3] Bacon (1991) was the first to use the term ‘rockets and feathers’ to describe the pattern of retail gasoline prices in the UK. This label suggests asymmetries in the sort-term adjustment to a cost change as well as in the number of periods needed for a complete adjustment.

Although the existing literature includes empirical studies on agri-food market integration in Sri Lanka, studies on price transmission focus primarily on wholesale and retail levels. However, integrating the farm level into these studies is crucial for a comprehensive analysis, considering both downstream (retail-wholesale) and upstream (farm-wholesale) segments of the value chain. Furthermore, no existing study analysed the price transmission process in the Sri Lankan rice value chain after the 2022 price shock.

3. Materials and methods

3.1. Context

The spatial analysis includes ten market locations, chosen based to the importance of their wholesale markets in the national rice economy and to their geographic distribution to ensure national representativeness. Five of these markets are in rice-producing zones, while the other five are in zones with limited rice production (Table 1 and Figure 1).

Table 1: List of Markets

In producing zones	Not in producing zones	Climatic zones		
		Wet	Inter.	Dry
Ampara	Colombo	Colombo	Kurunegala	Ampara
Anuradhapura	Gampaha	Gampaha		Anuradhapura
Batticaloa	Jaffna	Kandy		Batticaloa
Kurunegala	Kandy			Jaffna
Polonnaruwa	Trincomalee			Polonnaruwa
				Trincomalee

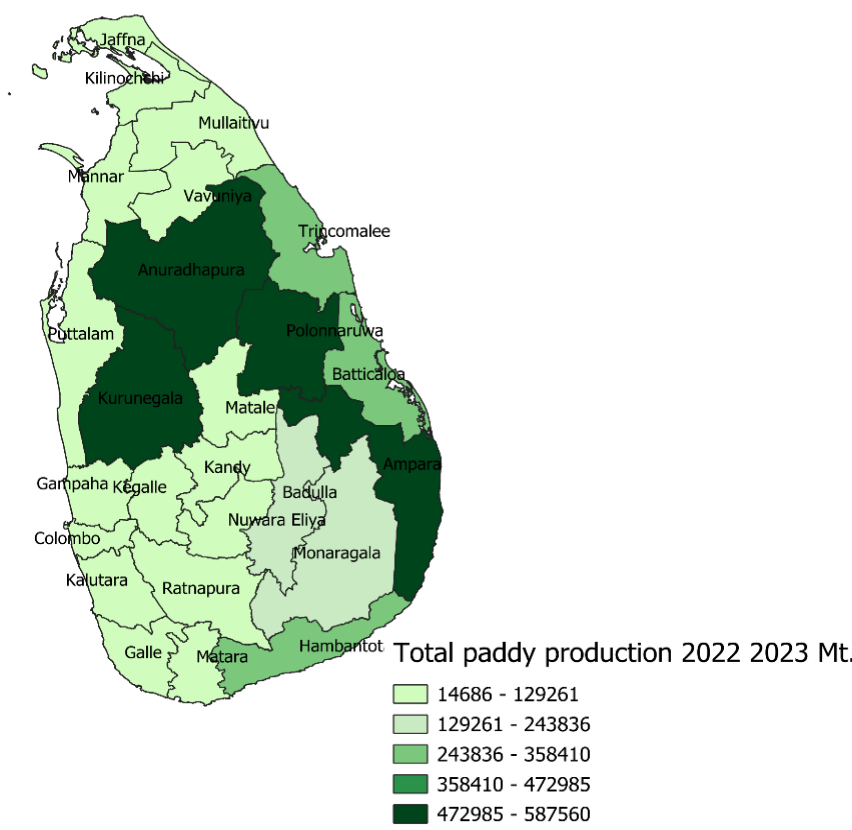

Figure 1: Paddy production map

Author's elaboration using paddy statistics, Department of Census Sri Lanka.

Nearly 86% of the marketable paddy surplus comes from the five selected markets, namely: Ampara, Anuradhapura, Batticaloa, Kurunegala and Polonnaruwa (Wijesooriya et al., 2020). Polonnaruwa is a major production zone and the largest rice processing area in Sri Lanka, with over 150 commercial paddy mills. About 19% of these mills process more than 20 metric tons per day, while 34% process between 8 and 20 metric tons per day (Priyadarshana and Wijesooriya, 2013). More than 75% of the mills are in Tamankaduwa and Hingurakgoda Divisional Secretariat (DS) divisions in Polonnaruwa. Small-scale mills are barely operational, with many converting to functions like paddy drying and collecting paddy bran and husk (Wijesooriya and Kuruppu, 2022

Paddy in Sri Lanka is cultivated under three irrigation regimes: major irrigation schemes, minor irrigation schemes, and rainfed. Major schemes cover areas larger than 80 hectares and have better-equipped control structures than minor schemes, with introduced water management practices. Major schemes are prevalent in the dry and intermediate zones, while rainfed methods are common in wetlands. Table 2 shows the percentage of rice cultivated under these schemes in the five selected production zones. Kurunegala, located in the intermediate wet zone, has the highest share of rainfed rice. There is a significant reduction in rainfed rice during the *Yala* season (April to September), driven by eastern production locations where the Yala season coincides with the dry season, unlike the west, which experiences the rainy season.

Table 2: Irrigation schemes

	Maha 2022 2023			Yala 2023		
	Major	Minor	Rainfed	Major	Minor	Rainfed
Ampara	75%	5%	20%	94%	4%	2%
Anuradhapura	46%	40%	14%	66%	34%	.
Batticaloa	42%	6%	52%	87%	13%	.
Kurunegala	22%	45%	33%	23%	44%	33%
Polonnaruwa	98%	1.5%	0.5%	88%	12%	.
Total	45%	25%	30%	63%	24%	13%

The remaining five wholesale markets are in highly populated areas with scarce rice production (Figure 1). The most important are the Pettah market in Colombo and the Marandagahamula wholesale market in Gampaha. The Pettah market, the main market in the capital city, is the most well-connected market due to its extensive railway and highway links. Gampaha's market is significant due to its location in the most populated area and proximity to Colombo, facilitating constant trading activities. These two markets will be central in the spatial analysis to study their interactions with regional markets.

The study focuses on the Nadu rice variety, the most consumed rice variety in Sri Lanka, with an average household monthly consumption exceeding 10 kilograms (Department of Census and Statistics, 2019). The Nadu variety is the most consumed rice variety in almost all market locations, except in Colombo, where the Samba short-grain variety is slightly more favoured, and Jaffna, where red rice is more commonly consumed (Figure 2). Dietary patterns in Sri Lanka are influenced by the country’s multi-ethnic cultures, resulting in regional variations in food preferences. For instance, the Northern Province, predominantly inhabited by Tamils, shows higher wheat consumption compared to rice (Jayatissa et al., 2014). Despite these variations, Jaffna is included in this study due to its significance as a major city and its geographical position as the northernmost point of Sri Lanka, ensuring comprehensive coverage of the entire nation.

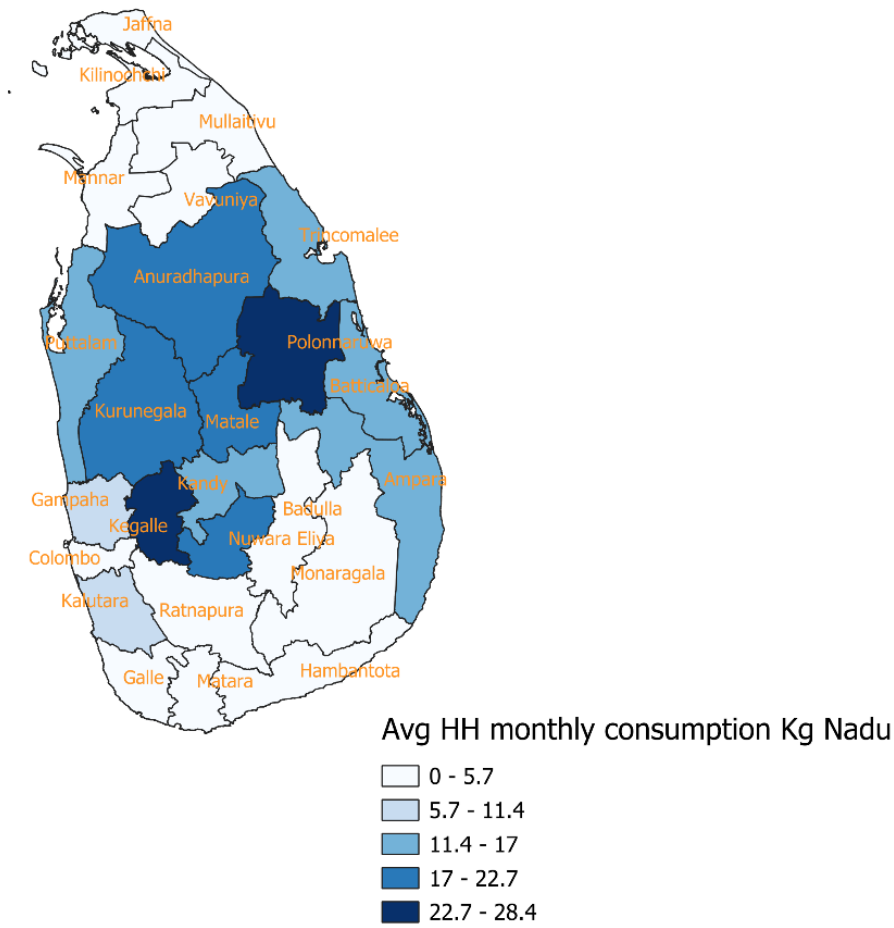

Figure 2: Average household monthly consumption Nadu

Author’s elaboration using 2019 hh survey , Department of Census Sri Lanka

Paddy farming in Sri Lanka is primarily conducted by small-scale farmers, each owning less than 0.4 hectares of land (De Silva et al., 2007), who collectively contribute to 70% of the country's total paddy production. However, the limited size of their landholdings and the lack of adequate storage facilities disadvantage them when negotiating favourable prices for their produce (Gedara et al., 2015).

The current paddy purchasing system involves both public and private sector participation (Wijesooriya et al., 2020). The main tool of the government's paddy procurement system is the Paddy Marketing Board (PMB). The PMB[4] played a crucial role after the civil war that lasted from 1983 to 2009. Paddy production in war-affected areas such as Batticaloa, Trincomalee, Ampara, and Mannar increased significantly after the war ended in 2009, resulting in a substantial surplus reaching the market from these regions and altering market dynamics. Consequently, the role of the PMB as a public entity has become more crucial in stabilizing the paddy market. The PMB has consistently increased its paddy purchases each season, reaching a record high in 2015, when it purchased 335,582 metric tons of paddy, accounting for 8% of the total paddy production and nearly 12% of the marketable surplus. The remaining 88% of the marketable surplus was purchased by the private sector, a trend that continues annually. In 2015, large-scale paddy millers received preferential credit facilities to modernize their mills with advanced technologies. These large-scale commercial millers, equipped with modern machinery, have significant market power in determining paddy and rice prices (Wijesinghe and Weerahewa, 2017).

Nowadays, the PMB is the main tool for the state to intervene in the paddy sector, fixing and maintaining guaranteed paddy prices, managing stocks, distributing grain, and disposing of paddy to stabilize the rice market. The government ceiling price plays a crucial role in balancing the seasonal consumer and producer price variation, persistent characteristics of Sri Lanka's paddy and rice market. As stated by Wijesooriya et al. (2020), rice prices in Sri Lanka exhibit an upward trend starting in September each year, peaking by December. Prices then decline rapidly until March and continue decreasing slowly until May. A second phase of price decline occurs in July and August with the Yala harvest. During December and January, rice prices reach unaffordable levels, severely impacting urban consumers and low-income groups. Conversely, in February and March, the sharp decline in paddy prices adversely affects marginalized farmers. The authors state that small-scale farmers prefer the government paddy purchasing program over private channels due to the higher price premiums offered during peak harvesting seasons. However, delays in the commencement of procurement by the PMB have restricted access for resource-poor farmers to the Government Paddy Purchasing Program (GPPP). Farmers complained that procurement delays lead to very low farm gate prices in the open market. They noted that timely procurement did not occur during the peak harvesting month in most major producing areas like Ampara and Batticaloa districts (Wijesooriya et al., 2020).

[4] The PMB was established in 1971 and it performed as the sole authorizer for paddy milling then in 1977 and 1995 were implemented market liberalization reforms that gave more relevance to the private sector. As stated by Mufeeth (2022) the rice market was prominently dominated by the private sector, and it handled more than 97 % of the paddy trade system from 1982 to 2019 whereas the PMB handled only 3 % of the market share. The market share of PMB was high in 1984 and it subsequently reduced until 1996. Then the paddy procurement activity of PMB stopped until 2008 (Mufeeth et al, 2022) The major objectives of the PMB procurement programme are to stabilize the farm gate prices, maintaining GP of paddy, buffer stock management, and grain distribution and disposal of paddy in order to stabilize the rice market. In general, the government imposed a ceiling of 2,500 kg of paddy from an individual farmer. Therefore, small-scale farmers opted for the government schemes. However, farmers who cultivate on a larger scale (nearly three or more acres) and producing marketable surplus beyond 2500kg sold to PMB and to the private sector (Wijesooriya et al. 2020).

3.2. Data

This study utilizes weekly price data for the Nadu rice variety, spanning the period from 2008 to 2023, collected by the Hector Kobbekaduwa Agrarian Research Institute (HARTI). The dataset includes weekly crop prices at farmgate, wholesale, and retail levels, as well as information on market locations. Additionally, it encompasses statistics such as the average, minimum, and maximum price values, the currency used for pricing, and the units of sale. Importantly, the market locations are dispersed throughout the country, ensuring the dataset is nationally representative. In the spatial analysis, we focus exclusively on wholesale prices, while in the vertical analysis, we employ wholesale, retail, and farmgate prices to account for the integration and transmission across the entire value chain. The data are naturally log-transformed to facilitate interpretation and to bring extreme values closer to the mean.

3.3. Methodology

3.3.1. Series stationarity

The first step of the methodology will be the inspection of the stationarity of the series. To do so the Augmented Dickey–Fuller (ADF) test will be performed on the time-series to find out whether they were nonstationary in their levels and integrated in the same order I(d). If the series will not be stationary in levels the test on first differences will be performed. The ADF test belongs to a category of tests called ‘Unit Root Test’, which is the proper method for testing the stationarity of a time series. Unit root is a characteristic of a time series that makes it non-stationary. A key point is that, since the null hypothesis assumes the presence of unit root (and thus of non-stationarity), the p-value obtained should be less than the significance level in order to reject the null hypothesis. The ADF test consist of estimating equation (1) below:

$$\Delta y_t = \beta_0 + \beta_t + \rho Y_{t-1} + \Sigma_{j=1}^{k} d_j \Delta Y_{t-j} + \varepsilon_t \qquad (1)$$

where Δy_t represents the first difference of the time series y_t . The first difference is the change in the value of the time series between time points t and t-1. It is calculated as $y_t - y_{t-1}$. β_t represents the coefficient of linear trend allowing for a linear trend in the data. $\Sigma_{j=1}^{k} d_j \Delta y_{t-1}$ represents the sum of lagged first differences of the time series from *t*-1 backward up to lag "k." In other words, it accounts for the influence of past differences on the current difference. The coefficients d_j are parameters to be estimated. ε_t is the error term or the white noise component of the model. It represents the random fluctuations in the time series that cannot be explained by the previous terms in the equation. Equation 1 tests the null hypothesis of a unit root ($\rho = 0$) against a stationary alternative ($\rho < 0$).

3.3.2. Series cointegration

To study the spatial and vertical cointegration of Nadu rice in Sri Lanka, we will employ both the Engle and Granger and Johansen cointegration tests. The Engle and Granger test is a pairwise test designed to assess cointegration between pairs of time series. For instance, we can analyze the cointegration between two locations or between two levels of the value chain, but it cannot examine cointegration among three levels of the value chain. In the Engle and Granger method, one variable is regressed on another to obtain residuals, and then an Augmented Dickey-Fuller

(ADF) test is conducted on the residuals. If the residuals are stationary, this suggests cointegration between the variables.

In contrast, the Johansen cointegration test is a statistical procedure used to assess the presence and number of long-term relationships, known as cointegrating vectors, among multiple time series variables. It is commonly applied in econometrics to determine whether variables move together in the long run. The test operates by estimating a vector autoregressive (VAR) model and, through a series of eigenvalue tests, determines the number of cointegrating relationships within the system. This analysis is particularly valuable for understanding the equilibrium associations between economic variables, such as price and quantity, in scenarios where traditional correlation or regression methods may not capture the underlying, persistent relationships over time. Unlike the Engle-Granger method, the Johansen test can accommodate more than two price series in the analysis, allowing us to study the interplay between farmgate, wholesale, and retail agricultural prices.

Deb et al. (2020) explain that the Johansen procedure helps to determine and identify the co-integrating vectors. The number of co-integrating vectors (r) should be less than the number of variables. In the vertical supply chain, as we are dealing with three distinct price series and thus, the number of co-integrating vectors should be less than three that is 0 ≤ r ≤ 3. Two statistics, namely eigenvalues and trace statistics are used in the Johansen test. Both tests consider the null hypothesis that there are maximum r co-integrating vectors and the procedure for determining the number of co-integrating vectors follows a sequential procedure. First, the null hypothesis H_0 (r = 0) against alternative hypothesis H_1 (r ≥ 1) is tested. If this null is not rejected, then it is concluded that there are no co-integrating vectors among the n variables. If H_0 (r = 0) is rejected, then it is concluded that there is at least one co-integrating vector, and the process proceeds to test H_0 (r ≤ 1) against H_1 (r ≥ 2). If this null is not rejected, then it is concluded that there is only one co-integrating vector. The criterion of estimating the number of co-integrating equations is to accept the first co-integration rank, r for which the null hypothesis is not rejected.

3.3.3.Granger Causality

Giving that in the vertical analysis we are working with three distinct prices the three variables will be paired to analyse the causal relationship between producer-wholesaler and wholesaler-consumer, so that, price leadership could be identified for the upstream (farm-wholesale) and downstream (retail-wholesale) market along the vertical supply chain, respectively. After these causality tests the study will find out the pairwise asymmetry for both upstream and downstream markets for the upstream (farm-wholesaler) market we can consider the following two equations, where each of the two variables is considered as the dependent variable.

$$\Delta F_t = \mu_1 + \Sigma_{i=1}^{k} \beta_{i(w)} \Delta W_{t-i} + \Sigma_{i=1}^{k} \beta_{j(f)} \Delta F_{t-j} + \alpha_1 Z_{t-1} + \varepsilon_{t,1} \qquad (2)$$

$$\Delta W_t = \mu_2 + \Sigma_{i=1}^{k} \beta_{i(w)} \Delta W_{t-i} + \Sigma_{i=1}^{k} \beta_{j(f)} \Delta F_{t-j} + \alpha_2 Z_{t-1} + \varepsilon_{t,2} \qquad (3)$$

For downstream (retail-wholesale) markets the following two equations are considered where each of the two variables is being taken as the dependent variable.

$$\Delta R_t = \mu_1 + \Sigma_{i=1}^{k}\theta_{i(w)}\Delta W_{t-i} + \Sigma_{j=1}^{l}\theta_{j(f)}\Delta R_{t-j} + \alpha_3 Z_{t-1} + \varepsilon_{t,3} \quad (4)$$

$$\Delta W_t = \mu_2 + \Sigma_{i=1}^{k}\theta_{i(w)}\Delta W_{t-i} + \Sigma_{j=1}^{l}\theta_{j(R)}\Delta R_{t-j} + \alpha_4 Z_{t-1} + \varepsilon_{t,4} \quad (5)$$

where, β_i and β_j measure the short-run effect of previous movements in farm and wholesale prices on current farm price changes while and $\theta_{i(w)}$, $\theta_{j(f)}$ and $\theta_{j(R)}$measure the same for farmgate, retail and wholesale prices on current retail price changes, Z_{t-1} is the lagged error correction term (ECT) for each equation, and *F*, *W* and *R* indicate the farm, wholesale and retail price, respectively. On the other hand, in the spatial part of the analysis we will test Granger causality between the two central markets , Colombo and Gampaha, and the various regional markets.

3.3.4. Adjustment along the chain

A further step will be the implementation of a VECM to capture the magnitude and speed of adjustment along the various value chains. This step will be crucial to detect the presence and the direction of APT. VECM introduces an error correction term, which represents the adjustment process when variables deviate from their long-term equilibrium. This term captures short-term dynamics and is based on the differences (or changes) between the non-stationary variables and their cointegrating relationship. The equations below describe the long-run equilibrium relationship between farm-wholesale and wholesale-retail prices assuming that the wholesale price could be considered exogenous :

$$F_t = \beta_0 + \beta_1 W_t + \Psi T + \varepsilon_t \quad (6)$$

$$R_t = \theta_0 + \theta_1 W_t + \varphi T + \vartheta_t \quad (7)$$

where F is farm or producer price, W is wholesale price, R is retail price, T is the time trend variable and ε is Gaussian white noise error term for the respective equation. The short-run dynamic price adjustments modified by an ECT are specified in terms of a typical error correction model (ECM):

$$\Delta F_t = \mu_1 + \Sigma_{i=1}^{k}\beta_{i(f)}\Delta F_{t-i} + \Sigma_{i=0}^{l}\beta_{j(w)}\Delta W_{t-j} + \alpha_1\hat{\varepsilon}_{t-1} + \varepsilon_t \quad (8)$$

$$\Delta R_t = \mu_1 + \Sigma_{i=1}^{k}\theta_{i(r)}\Delta R_{t-i} + \Sigma_{i=0}^{l}\theta_{j(w)}\Delta W_{t-j} + \alpha_2\hat{\vartheta}_{t-1} + \omega_t \quad (9)$$

where, β_i and β_j measure the short-run effect of previous movements in farm and wholesale prices on current farm price changes while $\theta_{i(r)}$ and $\theta_{j(w)}$ measure the same for retail and wholesale prices on current retail price changes. While α_1 and α_2 measure the speed of the adjustment to perturbations in long-run equilibrium; $\hat{\varepsilon}_{t-1}$ and $\hat{\vartheta}_{t-1}$, the ECM terms, measure the size of last periods departure (price perturbation) from long-run equilibrium where,

$\hat{\varepsilon}_{t-1} = F_{t-1} - \beta_0 - \beta_1 W_{t-1} - \psi\mathrm{T}$ and $\hat{\vartheta}_{t-1} = R_{t-1} - \theta_0 - \theta_1 W_{t-1} - \varphi\mathrm{T}$.

The VECM can be modified to account for seasonality. We know that in Sri Lanka there are two agricultural seasons the primary one is Maha while the secondary one is Yala. It is well known that seasonality influences the supply and thus the price of agricultural commodities especially in the case of lack of storage facilities. This is largely the case for Sri Lanka for the paddy rice supply chain. Indeed, Gedara et al. (2015) state that farmers' small landholding size and their lack of storage facilities makes them disadvantaged when bargaining a good price for their product. Consequently, after harvesting they tend to sell the harvest, without any delay. This results in a surplus of paddy supply in the market during harvesting season, which pushes prices to a lower level. In contrast, prices are high during the off season due to the shortage of supply. As previously mentioned, these dynamics are moderated by governmental interventions and pricing schemes. However, the overall impact is also contingent upon the timeliness of these government actions. Amikuzuno and von Cramon-Taubadel (2012) propose an extension of the VECM equation to account for seasonality. This extension allows the price adjustments and error correction term to differ between the seasonal regimes. In our case we can specify two dummies one for *Maha* and the other for *Yala* that are equal to 1 when t belongs to regime i where i = {*Maha*, *Yala*}.

$$\Delta F_t = \mu_1 + \Sigma_{i=1}^{k} \beta_{i(f)} \Delta F_{t-i} + \Sigma_{i=0}^{l} \beta_{j(w)} \Delta W_{t-j} + \begin{pmatrix} \alpha_{1maha} \\ \alpha_{1yala} \end{pmatrix} \hat{\varepsilon}_{t-1} + \varepsilon_t \qquad (10)$$

$$\Delta R_t = \mu_1 + \Sigma_{i=1}^{k} \theta_{i(r)} \Delta R_{t-i} + \Sigma_{i=0}^{l} \theta_{j(w)} \Delta W_{t-j} + \begin{pmatrix} \alpha_{2maha} \\ \alpha_{2yala} \end{pmatrix} \hat{\vartheta}_{t-1} + \omega_t \qquad (11)$$

3.3.5.Asymmetric Price Transmission

To detect the presence and direction of Asymmetric Price Transmission we will employ the Non Linear Autoregressive distributed Lags model (NARDL). The model was developed by Shin et al. (2014) who expanded the Autoregressive Distributed Lag model (ARDL) to a nonlinear framework in which short- and long-run nonlinearities are introduced via positive and negative partial sum decompositions of the explanatory variable. NARDL models capture asymmetric price transmission both in speed and in magnitude by incorporating different adjustment coefficients for positive and negative shocks. The NARDL is preferred to the asymmetric ECM because the latter is only able to capture the speed of time in asymmetric price transmission, and not the magnitude (Meyer & Cramon-Taubadel, 2004).

We start by looking at the standard Autoregressive Distributed Lag ARDL (p,q), co-integration model (Pesaran and Shin, 1995) where p is the dependent variable q is the independent variable and we have two time series $\{y_t\}$ and $\{x_t\}$ (t = 1, 2, ..., T). This model has the following form:

$$\Delta_{yt} = \alpha_0 + \rho y_{t-1} + \theta x_{t-1} + \gamma z_t + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-1} + \sum_{j=0}^{q-1} \pi_j \Delta y_{t-1} + \varepsilon_t \qquad (12)$$

Shin et al. (2014) introduced the Nonlinear Autoregressive Distributed Lag (NARDL) model, where $\{x_t\}$ is decomposed into its positive and negative partial sums, as follows:

$$x_t = x_0 + x_t^{+} + x_t^{-} \qquad (13)$$

where

$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max(\Delta_{j,} 0)$ (14)

$x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min(\Delta_{j,} 0)$ (15)

Then the long run equilibrium relationship can be written as:

$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t$ (16)

Shin et al. (2014) demonstrated that by integrating equation (14) with the ARDL (p,q) model (10), the NARDL (p,q) model is derived. In this model, β^+ and β^- represent the asymmetric long-run parameters associated with positive and negative changes in {xt} , respectively.

$\Delta y_t = \alpha_0 + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-1} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + e_t$ (17)

where:

$\theta^+ = -\rho/\beta^+$ and $\theta^- = -\rho/\beta^-$

The NARDL model facilitates the detection of Asymmetric Price Transmission (APT) in both the long and short run. It enables us to determine whether the welfare transfer, resulting from this inefficiency, has temporary or permanent effects. In terms of magnitude, Asymmetric Price Transmission (APT) illustrates the response of output prices to changes in input prices (Gervais, 2011). The presence of APT in magnitude is interpreted by the differing responses of output prices to increases and decreases in input prices over the long term (Fousekis et al., 2016). This phenomenon indicates the existence of permanent welfare transfers (Meyer & Cramon-Taubadel, 2004).Independent variables are assigned based on the results of the Granger causality test. For instance, the retail price is treated as the dependent variable, while the wholesale price serves as the independent variable. Utilizing the NARDL model, we can ascertain whether retail prices respond symmetrically to positive and negative shocks in wholesale prices.

4. Results

4.1. Spatial analysis

4.1.1. Spatial Descriptives

The table below presents the average price of 1 kilogram of Nadu rice in Sri Lankan rupees across selected markets. The table shows that rice prices surged dramatically in all markets in 2022. In 2023, these prices remained significantly high, with some markets experiencing further increases. The peak price in 2022 was observed in Jaffna, with an average price of 219 rupees per kilogram.

Table 3: Mean price 1 Kg./Rs in the markets.

Market	2018	2019	2020	2021	2022	2023
Ampara	85.18	85.34	95.96	108.90	199.24	194.28
Anuradhapura	83.75	87.31	93.02	116.54	200.14	203.76
Batticaloa	82.22	82.72	105.41	106.91	206.41	196.45
Colombo	80.59	87.08	95.27	110.52	187.26	187.32
Gampaha	82.85	86.45	93.57	110.48	191.29	194.27
Jaffna	88.45	76.09	95.34	128.88	219.86	192.63
Kandy	82.26	85.26	94.89	108.53	189.54	194.72
Kurunegala	81.86	85.73	91.91	110.21	196.07	192.74
Polonnaruwa	89.05	89.89	96.66	114.34	199.66	211.91
Trincomalee	80.47	79.34	96.06	132.83	195.50	187.96

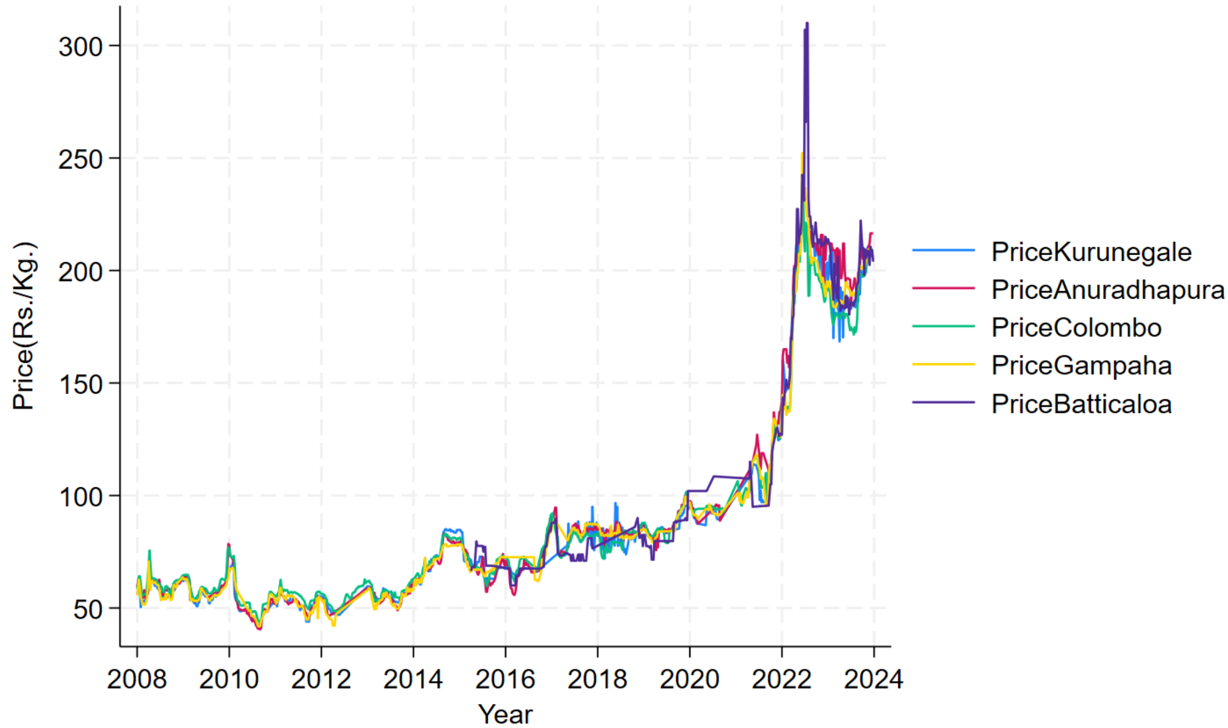

Figure 3: Plot of selected markets.

Author's elaboration using HARTI data

The plot illustrates that the price series across different markets exhibit a long-run co-movement, suggesting the presence of cointegration. Additionally, it indicates that the series are non-stationary at their levels. To formally validate this observation, it is necessary to apply the Augmented Dickey-Fuller (ADF) test. The graph highlights a significant price spike that occurred in 2022, which persisted into 2023, corroborating the findings from the descriptive statistics. The mean prices of Nadu rice for all markets in the country in 2022 are visually presented in Figure 4 below. The figure does not reveal a clear pattern in the price spike for producing versus deficit regions. However, it shows that the west coast of the country, particularly the area near Colombo, had an average Nadu price slightly lower than the rest of the country.

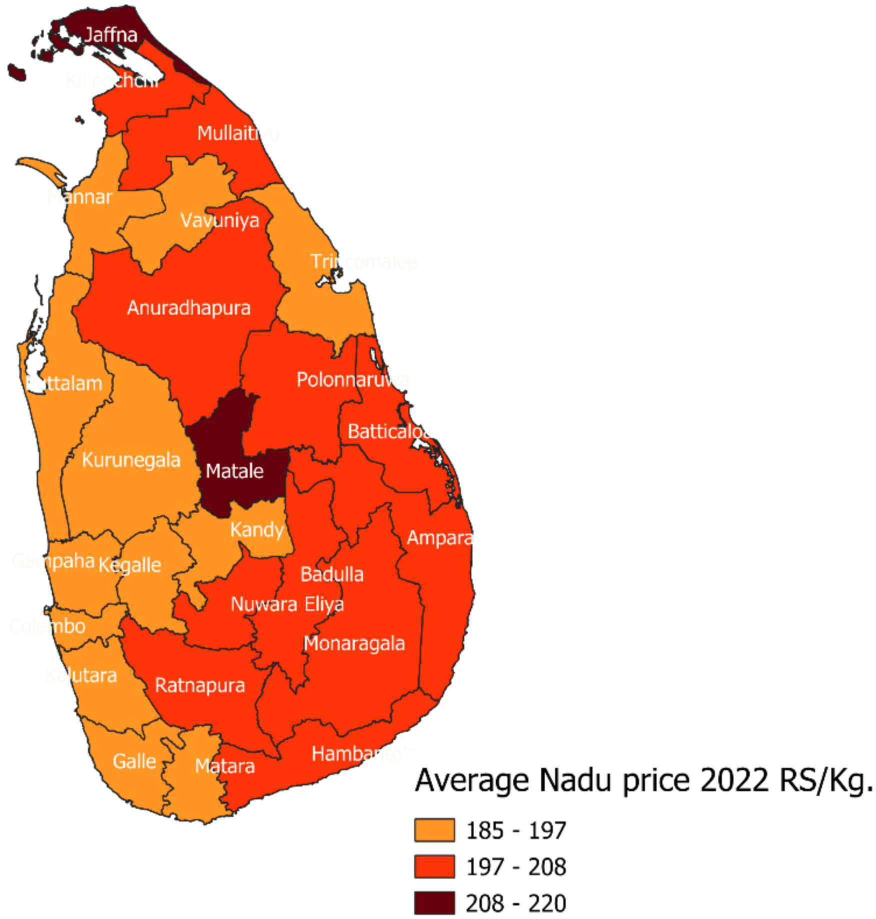

Figure 4: Average Nadu Price 2022

Author's elaboration using HARTI data

4.1.2. Stationarity in the markets

The first step of the analysis is the inspection of the stationarity of the series that was conducted running the ADF test. The ADF test belongs to a category of tests called 'Unit Root Test', the null hypothesis is that the series contains a unit root and thus is not stationary while the alternative hypothesis is that the variable of interest is stationary. Table 2 presents the results of this unit root test for the natural logarithm of the price series in the ten selected markets. The number in parentheses indicates the lag length that is selected following the Akaike Information Criterion (AIC). The Akaike Information Criterion (AIC) is a statistical tool used to compare the goodness of fit of various time series models with differing numbers of lags. It assesses the relative quality of a statistical model based on its ability to fit the data while avoiding overfitting. The AIC balances the trade-off between model complexity (i.e., the number of parameters) and goodness of fit (i.e., the ability to explain the data). The results suggest that in all the locations the price series have a unit root in level. Indeed for the data in level the estimated values do not exceed the critical values and thus, we cannot reject the null hypothesis of presence of a unit root. However, the price series become stationary after taking the first differences and thus are integrated of order one I(1), containing only one unit root.

Table 4: Spatial ADF

Markets	Order	T-value	Remarks
Ampara (2)	I = 0	-1.71	Nonstationary
	I = 1	-17.68***	Stationary
Anuradhapura (14)	I = 0	-2.23	Nonstationary
	I = 1	-12.52***	Stationary
Batticaloa (4)	I = 0	-2.91	Nonstationary
	I = 1	-9.38***	Stationary
Colombo (4)	I = 0	-1.75	Nonstationary
	I = 1	-8.36***	Stationary
Gampaha (4)	I = 0	-1.95	Nonstationary
	I = 1	-8.19***	Stationary
Jaffna (4)	I = 0	-1.96	Nonstationary
	I = 1	-11.38***	Stationary
Kandy (6)	I = 0	-1.89	Nonstationary
	I = 1	-11.08***	Stationary
Kurunegala (24)	I = 0	-2.09	Nonstationary
	I = 1	-5.51***	Stationary
Polonnaruwa (3)	I = 0	-2.05	Nonstationary
	I = 1	-16.71***	Stationary
Trincomalee (2)	I = 0	-2.07	Nonstationary
	I = 1	-12.03***	Stationary

The critical values are -3.988(1%) , -3.428 (5%), -3.130 (10%).
The values in parenthesis represents the lag length based on Akaike Information Criterion (AIC).

4.1.3. Spatial cointegration

In this subsection, we present the results of the pairwise cointegration analysis, which was conducted using the Engle and Granger method. This method involves regressing one variable on another to obtain residuals, followed by conducting an Augmented Dickey-Fuller (ADF) test on these residuals to determine their stationarity. If the residuals are stationary, it suggests cointegration between the variables. The table shows that cointegration exists in all the market pairs presented, as all estimated values are significant at the 1% level, allowing us to reject the null hypothesis of a unit root. Consequently, we can conclude that there is pairwise cointegration among all the wholesale markets under consideration. This implies that wholesale prices across different markets will move together in the long run, despite potential short-run deviations.

Table 5: Spatial Engle and Granger

Market pairs	T value	P value
Ampara - Anuradhapura(3)	-15.29***	0.000
Ampara - Batticaloa (5)	-19.03***	0.000
Ampara - Colombo(3)	-14.94***	0.000
Ampara - Gampaha(2)	-15.23***	0.000
Ampara - Kandy(4)	-14.28***	0.000
Ampara - Kurunegala(11)	-10.47***	0.000
Ampara - Jaffna(4)	-13.91***	0.000
Ampara - Polonnaruwa(3)	-14.91***	0.000
Ampara -Trincomalee(3)	-11.49***	0.000
Anuradhapura - Batticaloa(4)	-13.01***	0.000
Anuradhapura - Colombo(4)	-13.81***	0.000
Anuradhapura - Gampaha(3)	-17.13***	0.000
Anuradhapura - Kandy(3)	-17.98***	0.000
Anuradhapura - Kurunegala(4)	-16.63***	0.000
Anuradhapura - Jaffna (4)	-17.76***	0.000
Anuradhapura - Polonnaruwa(4)	-15.00***	0.000
Anuradhapura - Trincomalee(3)	-12.20***	0.000
Batticaloa - Colombo(8)	-8.78***	0.000
Batticaloa - Gampaha(10)	-7.38***	0.000
Batticaloa - Kandy(4)	-14.67***	0.000
Batticaloa - Kurunegala(5)	-10.71***	0.000
Batticaloa - Jaffna(4)	-10.43***	0.000
Batticaloa - Polonnaruwa(18)	-5.25***	0.000
Batticaloa - Trincomalee(4)	-11.02***	0.000
Colombo - Gampaha (4)	-15.66 ***	0.000
Colombo - Kandy(9)	-12.47***	0.000
Colombo - Kurunegala(4)	-16.73***	0.000
Colombo - Jaffna(4)	-12.65***	0.000
Colombo - Polonnaruwa(4)	-17.15***	0.000
Colombo - Trincomalee(3)	-11.15 ***	0.000
Gampaha - Kandy(4)	-16.01***	0.000
Gampaha - Kurunegala(4)	-16.15***	0.000
Gampaha - Jaffna(4)	-12.49***	0.000
Gampaha - Polonnaruwa(3)	-21.18***	0.000
Gampaha - Trincomalee(3)	-13.38***	0.000
Kandy - Kurunegala(4)	-16.31***	0.000
Kandy -Jaffna(4)	-12.69***	0.000
Kandy - Polonnaruwa (4)	-12.43***	0.000
Kandy - Trincomalee(4)	-13.24***	0.000
Kurunegala - Jaffna(3)	-14.17***	0.000
Kurunegala - Polonnaruwa(5)	-15.82***	0.000
Kurunegala - Trincomalee(4)	-11.11***	0.000
Jaffna - Polonnaruwa (4)	-13.54***	0.000
Jaffna - Trincomalee(3)	-16.23***	0.000
Polonnaruwa - Trincomalee(3)	-11.31 ***	0.000

Johansen test allows simultaneous analysis of multiple cointegrating relationships. Also the Johansen method confirm the existence of cointegration among the markets. Indeed both Trace statistics and maximum eigen values exceed the critical values for more than one cointegrating equation. Both tests confirm long run cointegration among all markets. Thus, even if they may deviate in the short run price series in the various markets move together in the long run. The presence of a cointegration relationship justifies the necessary condition for applying VECM to the market pairs to analyse the nature of price transmission between central and regional markets.

Table 6: Spatial Johansen

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value 5%	Maximum Eigenvalue	Critical value 5%
0	210	10403.54	.	295.171	233.13	66.77	62.81
1	229	10436.93	0.137	228.392	192.89	61.056	57.12
2	246	10467.45	0.126	167.336	156.00	39.313	51.42
3	261	10487.11	0.083	128.023	124.24	37.181	45.28
4	274	10505.70	0.078	90.841*	94.15	29.228	39.37
5	285	10520.32	0.062	61.612	68.52	22.214	33.46
6	294	10531.42	0.047	39.397	47.21	16.146	27.07
7	301	10539.51	0.035	23.251	29.68	14.782	20.97
8	306	10546.89	0.032	8.469	15.41	8.402	14.07
9	309	10551.09	0.018	0.066	3.76	0.066	3.76
10	310	10551.12	0.000	.	.	.	.

4.1.4. Spatial Granger causality

To further understand price leadership among the various wholesale markets, it is necessary to conduct Granger causality tests. These tests help identify predictive relationships between prices in geographically dispersed markets. The hypotheses tested are that Market A does not Granger-cause Market B and that Market B does not Granger-cause Market A. Rejecting both hypotheses indicates bidirectional causality. We examined the relationships between the Colombo market and nine other markets, then replicated the analysis using Gampaha as the central market. The selection of Colombo and Gampaha as central markets was informed by discussions with colleagues and stakeholders in Sri Lanka. The Colombo market, Pettah, is a major trade hub in the capital city, well-connected by highways and railways to all other locations. Conversely, Gampaha is another significant wholesale market due to its large population and proximity to the capital.

The results, presented in Table 7, show that Colombo exhibits bidirectional price causality with almost all markets, except for Trincomalee, which is Granger-caused by Colombo's prices but does not Granger-cause them. Indeed, with the exception of Trincomalee, we can always reject both hypotheses of lack of causation between markets. The results for Gampaha as a central market are very similar. Gampaha shows bidirectional causality with all the markets. Thus, we can conclude that, with the exception of Trincomalee, there is no market dominance by the considered central market over regional markets in rice price formation. The results are contained in Tables 7 and 8 below and are graphically represented in figure 5 and 6.

Table 7: Spatial Granger causality Colombo → Regional

Market Paired with Colombo	Colombo market	Regional markets	Direction
Ampara	40.79***	13.239***	Bidirectional
Anuradhapura	28.01***	23.64***	Bidirectional
Batticaloa	53.764**	10.93***	Bidirectional
Gampaha	3.96**	12.32***	Bidirectional
Jaffna	23.44***	18.01***	Bidirectional
Kandy	44.82***	5.43***	Bidirectional
Kurunegala	5.30**	23.43***	Bidirectional
Polonnaruwa	22.14***	9.44***	Bidirectional
Trincomalee	30.24***	1.4195	Colombo → Trincomalee

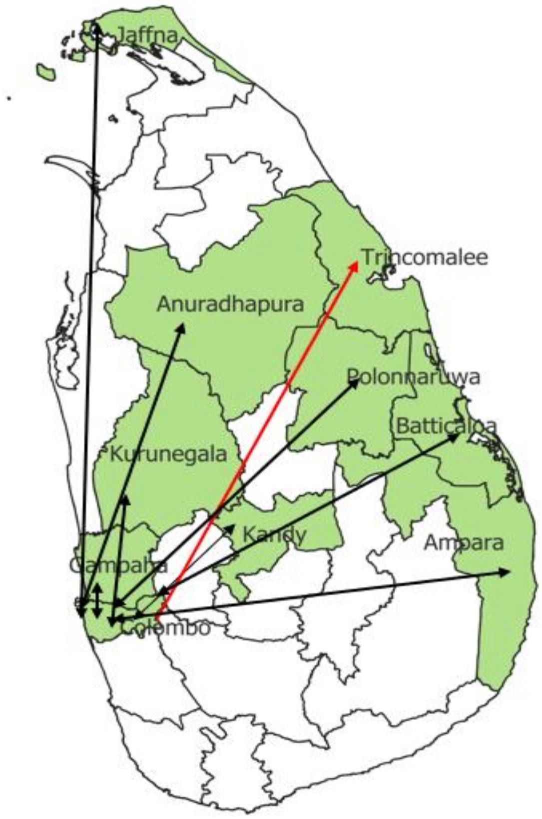

Figure 5: Map Granger causality Colombo

Table 8: Spatial Granger causality Gampaha → Regional

Market Paired with Gampaha	Gampaha market	Regional markets	Direction
Ampara	36.78***	35.25***	Bidirectional
Anuradhapura	34.66***	49.79 ***	Bidirectional
Batticaloa	31.779***	10.24***	Bidirectional
Colombo	13.813***	44.25***	Bidirectional
Jaffna	13.121***	29.37***	Bidirectional
Kandy	36.146***	18.72***	Bidirectional
Kurunegala	26.371*	42.37***	Bidirectional
Polonnaruwa	69.18***	23.60***	Bidirectional
Trincomalee	7.31 ***	26.06***	Bidirectional

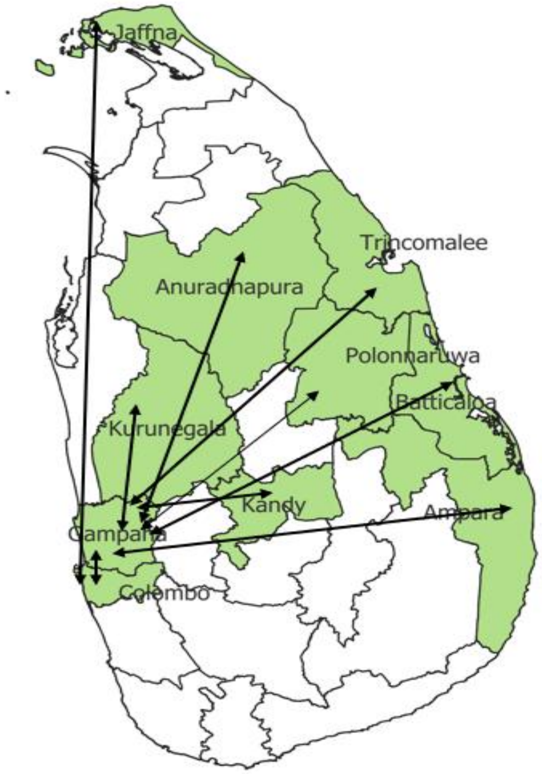

Figure 6: Map Granger causality Gampaha

4.1.5. Spatial price transmission

In this section, the results of the Error Correction Model (ECM) are presented. The ECM incorporates an Error Correction Term (ECT) that characterizes the process through which variables return to their long-term equilibrium following deviations. This model is particularly adept at capturing short-term dynamics within market interactions. The analysis focuses on Colombo and Gampaha as central markets to study the price transmission dynamics among other markets.

The table below features ECT values, half-lives, distances between market pairs in kilometres, and long-run coefficients, which can be interpreted as long-term elasticity. The observed long-run coefficients, approaching unity and statistically significant at the 1% level, suggest a high degree of long-term market integration. Statistically significant ECTs indicate that, when the system is in disequilibrium, there is a concerted effort to restore equilibrium. ECT values serve as indicators of adjustment speed; for instance, Anuradhapura exhibits an ECT of 0.07, implying that approximately 7% of the price adjustment to Colombo occurs within a week. Conversely, Ampara shows an ECT of 0.04, indicating a 4% adjustment within the same timeframe. A half-life represents the time needed for a shock to diminish by half its initial impact. For example, the 9.91-week half-life between Colombo and Anuradhapura signifies that half of any disequilibrium between these markets is typically corrected within approximately 10 weeks. Conversely, Jaffna has a half-life of 23.10 weeks, meaning half of the disequilibrium to Colombo prices is corrected in a little over 23 weeks.

The results indicate that ECTs are generally higher for regional markets compared to Colombo, averaging 4% for Colombo markets and 6% for regional markets. This 2% disparity signifies a faster rate of price adjustment in regional markets when correcting disequilibria to Colombo, compared to the reverse process. Moreover, higher ECT values in regional markets correspond to shorter half-lives; specifically, regional markets exhibit a mean half-life of 13 weeks, whereas the Colombo market averages 22 weeks. This finding aligns with the insights of Von-Cramon Taubadel and Meyer (2004), who state that prices at a central market, by virtue of its size and centrality in the information network, may be less responsive to price changes in peripheral markets than vice versa.

Jaffna and Trincomalee demonstrate the lowest ECTs, correcting 3% of Colombo-related disequilibrium weekly. The influence of market distance on adjustment speed is evident, as more distant markets such as Ampara, Jaffna, and Trincomalee exhibit lower ECTs and higher half-lives. This confirms that price transmission between remote markets occurs at a slower pace (Barrett and Li, 2002). However, the precise relationship between market distance and adjustment level remains undefined. Interestingly, Kandy, despite not being the nearest market to Colombo, demonstrates the highest adjustment speed.

Similar patterns emerge when Gampaha is considered the focal point of the adjustment process. The long-run coefficients are close to unity and statistically significant at the 1% level, underscoring the high level of market integration over time. Additionally, all ECTs are statistically significant in this context, with regional markets showing a higher average ECT compared to the central market. This trend also holds true for half-lives, although the differences in average ECTs and half-lives are less pronounced compared to the Colombo scenario. Specifically, the mean ECT is 5% for the central market and 6% for regional markets, indicating a 1% difference in the rate of price transmission and spatial integration of rice markets.

Once again, the relationship between market distance and adjustment speed is consistent, with Ampara, Jaffna, and Trincomalee exhibiting the slowest adjustment speeds. However, as observed previously, Kandy, Kurunegala, and Polonnaruwa stand out with the highest adjustment speed among these markets, further illustrating that distance alone does not precisely determine adjustment dynamics.

Table 9: Spatial VECM Colombo → Regional

Market	L-R coefficient	ECT C	Half-life C	ECT R	Half-life R	Distance (Kms)
Ampara	1.11***	-0.03***	23.10	-0.04***	17.32	412
Anuradhapura	1.10***	-0.07***	9.91	-0.07***	9.91	200
Batticaloa	1.08***	-0.03***	23.10	-0.06***	14	324
Gampaha	1.07***	-0.04***	17.32	-0.08***	8.66	40
Jaffna	1.05***	-0.02***	34.65	-0.03***	23.10	405
Kandy	1.04***	-0.05**	13.86	-0.13***	5.34	122
Kurunegala	1.07***	-0.07***	9.91	-0.09***	7.65	103
Polonnaruwa	1.10***	-0.02**	34.65	-0.11***	6.31	230
Trincomalee	1.06***	-0.02***	34.65	-0.03***	23.10	267
Average	.	0.04	17	0.06	14	.

Table 10: Spatial VECM Gampaha → Regional

Market	L-R coefficient	ECT G	Half-life G	ECT R	Half-life R	Distance (Kms)
Ampara	1.03***	-0.04***	17.32	-0.03***	23.09	318
Anuradhapura	1.03***	-0.08***	8.66	-0.07***	9.91	173
Batticaloa	1.06***	-0.03***	23.09	-0.04***	17.32	289
Colombo	0.93***	-0.08***	8.66	-0.05***	13.86	40
Jaffna	1***	-0.02	34.65	-0.02***	23.09	360
Kandy	0.98***	-0.08***	8.66	-0.08***	8.66	90
Kurunegala	1***	-0.07***	9.94	-0.08***	8.66	69
Polonnaruwa	1.03***	-0.04***	17.32	-0.08***	8.66	197
Trincomalee	1.03***	-0.03***	23.09	-0.02***	34.65	231
Average	.	0.05	16	0.05	16	.

4.2. Vertical analysis

4.2.1. Vertical descriptives

In the table below, the mean prices for 1 kg of Nadu rice, expressed in Sri Lankan rupees, are presented for wholesale, retail, and farmgate levels. The data exhibit the anticipated price hierarchy, with retail prices being the highest and farmgate prices the lowest. Notably, in 2022, there was a significant price spike across all three levels, with a marked increase compared to 2021.

Table 11: Mean price 1 Kg./Rs. along the chain

Prices	2018	2019	2020	2021	2022	2023
Wholesale	80.59	87.08	95.27	109.85	187.26	187.32
Retail	91.43	92.60	100.42	120.73	205.73	212.11
Farmgate	40.16	43.12	49.39	58.14	107.49	97.17

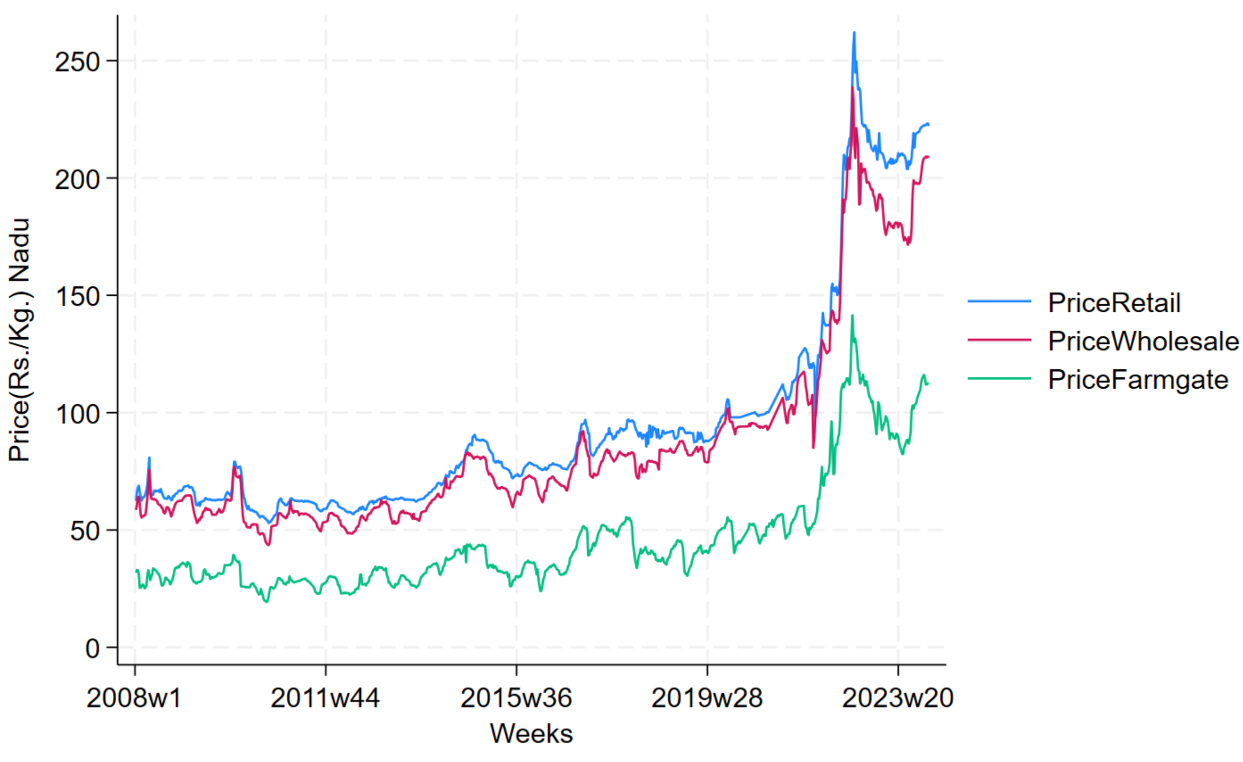

Figure 7 : Plot of the three prices

Author's elaboration using HARTI data

The price spike is confirmed by the graph above. In the first months of 2022 the three price series increased significantly and slightly decreased in 20223. The series seems to move together in the long run suggesting that we will find cointegration among them. From the graph we can also expect that the series will not be stationary in levels. Stationarity inspection is performed in the next section.

4.2.2.Stationarity along the chain

As expected the three price series are not stationary in levels, we cannot reject the null hypothesis of presence of a unit root. However, once we take first differences we can reject the null hypothesis of presence of a unit root and thus, we can conclude that the three price series are integrated of order 1 I(1).

Table 12: Vertical ADF

Markets	Order	T-value	P-value	Remarks
Wholesale(2)	I = 0	-2.466	0.3449	Nonstationary
	I = 1	-15.394 ***	0.00	Stationary
Retail (2)	I = 0	-1.748	0.729	Nonstationary
	I = 1	-15.892 ***	0.000	Stationary
Farmgate(2)	I = 0	-3.12	0.102	Nonstationary
	I = 1	-15.301 ***	0.00	Stationary

The critical values are -3.988(1%) , -3.428 (5%), -3.130 (10%).
The values in parenthesis represents the lag length based on Akaike Information Criterion (AIC).

4.2.3. Vertical cointegration

The table below presents the results of the Engle and Granger test for the various levels of the value chain. The Augmented Dickey-Fuller (ADF) test on the stationarity of the residuals successfully rejects the null hypothesis of a unit root for all three pairs of prices. The stationarity of the residuals obtained from regressing one price series on another confirms the presence of cointegration.

Table 13: Vertical Engle and Granger

Market Pairs	T- stat	P – value
Retail- Wholesale	-11.588 ***	0.00
Retail – Farmgate	-15.972 ***	0.00
Wholesale – Farmgate	-17.328***	0.00

The critical values are -3.988(1%) , -3.428 (5%), -3.130 (10%).
The values in parenthesis represents the lag length based on Akaike Information Criterion (AIC).

The presence of cointegration is confirmed also by the Johansen multivariate test. Indeed the trace statistics and the maximum eigenvalues exceed the critical values for more than one cointegrating equations. Once again, the presence of a cointegration relationship justifies the necessary condition for applying VECM to the value chain levels to analyse the nature of price transmission among them and to study short-term dynamics. Indeed, as stated by Gedara et al. (2015) cointegration between wholesale and retail markets suggests that these two price series are in a long-term equilibrium, meaning they do not diverge permanently over time. However, cointegration does not preclude short-term fluctuations in the price series. As Engle and Granger (1987) posited, while cointegrated variables may experience short-term divergence, an error correction mechanism facilitates the restoration of long-run equilibrium. The short-term dynamics of the integrated variables, along with the corresponding error correction process, can be analysed using an error correction model (ECM) (Gedara et al., 2015).

Table 14: Vertical Johansen

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value 5%	Maximum Eigenvalue	Critical value 5%
0	30	5800.507	.	103.132	29.68	65.756	20.97
1	35	5833.385	0.076	37.376	15.41	37.091	14.07
2	38	5851.931	0.0438	0.285*	3.76	0.285*	3.76
3	39	5852.073	0.000	.	.	.	.

4.2.4. Vertical Granger causality

From the Granger causality test, it appears that there is unidirectional price causality between each pair of prices in the rice market. In the upstream sector, farmgate prices determine wholesale prices, while in the downstream sector, wholesale prices Granger-cause retail prices. Specifically, Nadu prices, which are established at the upper level of the supply chain, flow downward, with farmgate prices leading other price levels. This causality pattern aligns with the broader understanding of price transmission in agricultural markets. Farmgate prices, reflecting production costs, are pivotal in determining wholesale prices. Wholesalers, acting as intermediaries, adjust their prices in response to farmgate costs and market expectations, which then impact retail prices. According to Tiwari (2012), wholesale prices generally cause retail prices because wholesalers adjust prices based on cost changes and market expectations, which retailers subsequently adopt. This process underscores the critical role of wholesalers in linking farmgate and retail prices. Additionally, Jones (1986) explains that this chain of causality is essential for maintaining market equilibrium, as it ensures that price changes at different market levels are transmitted efficiently. Overall, the sequence of causality, from farmgate to wholesale to retail, is crucial for market efficiency and price stability, ensuring that costs at the production level ultimately influence consumer prices.

Table 15: Vertical Granger Causality

Market Paired with Colombo	Wholesale	Retail	Farmgate	Direction
Retail – Wholesale	95.236 ***	.96822	.	Wholesale → Retail
Retail – Farmgate	.	0.53	52.89***	Farmgate → Retail
Wholesale – Farmgate	.58457	.	99.595 ***	Farmgate → Wholesale

4.2.5. Vertical price transmission

In this section, the results of the Vector Error Correction Model (VECM) are presented. The long-run coefficients are all statistically significant and close to unity, indicating that there is nearly perfect integration in the Nadu value chain in Sri Lanka over the long term. The error correction terms are also statistically significant, suggesting that the system, once in disequilibrium, tends to revert to an equilibrium state. The fastest adjustment is observed between the retail and wholesale prices, with half of the disequilibrium in the downstream segment corrected within 8 weeks, or approximately 8.5% of the short-run disequilibrium corrected within a week. Regarding the retail and farmgate levels, half of the disequilibrium is corrected in just over 14 weeks, with a weekly adjustment of almost 5% of retail prices to farmgate prices. Finally, in the upstream segment, half of the disequilibrium is corrected within 18 weeks, or approximately 3.7% of the short-run disequilibrium between wholesale and retail prices is corrected within a week. This may be due to government intervention in the rice sector and the presence of price ceilings. Indeed, guaranteed farmgate prices may reduce the speed of adjustment compared to a process where the price is solely determined by market forces. This guaranteed price is crucial, especially for smallholders and poor farmers, ensuring they receive a fair price during the harvesting season. After the study of aggregated price transmission the result for the disaggregated analysis in agricultural seasons is presented. Table 17 presents the Vector Error Correction Model (VECM) results for the main agricultural season, Maha. The long-run coefficients, closely approximating unity and statistically significant at the 1% level, indicate robust integration across the three levels of the supply chain over the long term. Additionally, the error correction terms (ECTs) are all negative and significant at the 1% level, indicating that the system endeavours to return to equilibrium when perturbed. The ECT magnitudes reveal a gradation in the speed of adjustment, with the slowest between farmgate and wholesale prices at only 2.6%, implying that half of the price disequilibrium between these levels takes more than 26 weeks to correct. This slower adjustment may be attributed to government-imposed ceiling prices during the peak harvest months of February and March, which follow the price peaks of January. Such ceiling prices, along with government purchasing schemes, suppress competitive forces and decelerate the adjustment process between producers and wholesalers. The significance of these interventions cannot be overstated, as they play a crucial role in ensuring that small-scale farmers receive equitable compensation for their produce during the harvest season. Table 18 delineates the results of the Vector Error Correction Model (VECM) for the secondary agricultural season, Yala. The analytical results maintain consistent signs and levels of statistical significance for both the long-run coefficients and the error correction terms (ECTs) as observed during the Maha season. Notably, the magnitude of the ECTs exhibits variance from the Maha season; specifically, the adjustment speed between wholesale and farmgate prices during Yala is more rapid, at 5.6%, with half of the disequilibrium resolved within approximately 12 weeks. This observation underscores a seasonally driven variation in adjustment speeds, suggesting that the slower adjustment observed in the aggregated VECM predominantly reflects the dynamics of the Maha season, wherein government interventions are more pronounced in response to significant price drops during peak harvest periods

Table 16: Vertical VECM

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	1.01***	-0.085***	8.15
Retail – Farmgate	0.98***	-0.048***	14.45
Wholesale – Farmgate	0.97***	-0.037***	18.76

Table 17 : Maha VECM

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	1.01***	-0.074***	9.03
Retail – Farmgate	0.98***	-0.036***	18.93
Wholesale – Farmgate	0.97***	-0.026***	26.25

Table 18 : Yala VECM

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	1.01***	-0.06***	11.25
Retail – Farmgate	0.99***	-0.037***	18.48
Wholesale – Farmgate	0.96***	-0.056***	12.08

Table 19 : Pre-Shock VECM (2019 to February 2020)

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	0.86***	-0.49**	1.17
Retail – Farmgate	0.62***	-0.04	17.33
Wholesale – Farmgate	0.70***	-0.06*	11.05

The results for the VECM analysis conducted for 2019 and the first two months of 2020 are presented in the table above. Beginning with the long-run coefficients, which, given the log-transformation of the data, can be interpreted as elasticities, all three coefficients are statistically significant at the 1% level. However, their magnitudes are considerably lower compared to the aggregated analysis. The long-run coefficient (LRC) of 0.86 for the retail–wholesale pair indicates moderate long-run integration, suggesting that 86% of wholesale price changes are transmitted to retail prices over time. This reflects a stable yet somewhat rigid downstream market, likely attributable to price stabilization policies such as retail price ceilings. Similarly, the LRC of 0.62

for the retail–farmgate pair points to weaker upstream integration, potentially due to government-mandated farmgate price controls that insulated farmers from market fluctuations. The LRC of 0.70 for the wholesale–farmgate pair denotes moderate integration, indicating that wholesale prices only partially reflect farmgate price changes.

Turning to the interpretation of the Error Correction Terms (ECTs), which represent the short-term dynamics when the system deviates from its long-run equilibrium and can be interpreted as adjustment speeds, we begin with the retail–wholesale pair. Here, we observe an extremely high, negative, and statistically significant error correction rate. During 2019 and the early months of 2020, retail prices corrected half of their disequilibrium with wholesale prices in just over a week, underscoring a remarkably fast adjustment process.

In contrast, the ECT between retail and farmgate prices is not statistically significant, marking the first occurrence of such a result in this analysis. A non-significant ECT suggests that short-run deviations from the long-run equilibrium are not effectively corrected, revealing weak short-run integration between retail and farmgate prices. This implies that changes in farmgate prices do not promptly influence retail prices, or vice versa. Several potential factors could explain this phenomenon. Policy interventions, such as government-mandated farmgate price controls or retail price ceilings, may insulate one level from short-term fluctuations. Furthermore, market frictions, including delays in transportation, processing, or supply chain coordination, may slow the transmission of price signals. Fragmented supply chains with multiple intermediaries further weaken the direct connection between farmgate and retail prices. Additionally, retailers' price stickiness, influenced by menu costs, contractual constraints, or strategic pricing behaviour, can delay adjustments. The absence of significant short-run adjustments implies reduced market efficiency, as persistent deviations suggest that price signals are not effectively transmitted. This result may also hint at asymmetry in price responses, where retail prices react differently to increases and decreases in farmgate prices. Ultimately, the insignificance of the ECT reflects structural and operational inefficiencies, suggesting that the market relies more heavily on long-run adjustments and highlighting the need for improvements in short-term price responsiveness.

Finally, examining the ECT between wholesale and farmgate prices, we observe that it is statistically significant at the 10% level, indicating that 6% of the disequilibrium between these two market levels is corrected within a week. While this adjustment speed is relatively slow, it suggests the presence of at least some short-run responsiveness, albeit limited, in the upstream segment of the supply chain.

Table 20 : COVID and Shock VECM (March 2020 to November 2022)

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	1.01***	0.00	-
Retail – Farmgate	0.94***	-0.10***	6.58
Wholesale – Farmgate	0.90***	-0.27***	2.51

Now, let us analyse the period that encompasses both the COVID-19 pandemic and the food price shock that significantly affected Sri Lanka. The table presents results for the period spanning from March 2020 to November 2022. Focusing on the long-run coefficients (LRCs), all are statistically significant at the 1% level and close to unity, indicating a high degree of long-run integration across the supply chain. The LRC for the retail–wholesale relationship is 1.01, which suggests a slight over-transmission, as retail prices rose disproportionately relative to wholesale prices. This phenomenon likely reflects retailer opportunism and heightened uncertainty during the crisis, where retailers took advantage of volatile conditions to increase margins.

The LRC between retail and farmgate prices is 0.94, indicating stronger long-run integration compared to the pre-COVID period. This could be due to reduced policy intervention insulating farmgate prices, as well as higher input costs for farmers, which pushed farmgate prices closer to retail prices. Finally, the LRC of 0.90 between wholesale and farmgate prices demonstrates strong integration, with wholesale prices closely tracking farmgate prices over the long run, reflecting the relatively direct nature of this upstream relationship.

Shifting focus to the Error Correction Terms (ECTs), the retail–wholesale pair exhibits a striking observation: the ECT is not only statistically insignificant but also virtually zero. An ECT of 0.00 suggests a complete breakdown in short-run adjustments, indicating that deviations from the long-run equilibrium between retail and wholesale prices were not corrected during the crisis. While this analysis is limited to price data and cannot definitively determine the cause, several plausible explanations emerge. The COVID-19 pandemic likely disrupted the alignment between wholesale and retail prices due to logistical bottlenecks, such as transportation delays, curfews, and supply chain interruptions. Furthermore, panic buying and sudden surges in retail demand may have prompted retailers to adopt temporary pricing strategies independent of wholesale price movements. In addition, the food inflation crisis and agricultural policy changes, such as the fertilizer import ban implemented in 2021, may have exacerbated these disruptions. The fertilizer ban caused a sharp decline in agricultural yields, including rice production, leading to supply shortages that likely distorted price transmission mechanisms. However, while these factors provide potential explanations, the absence of significant short-run adjustments suggests a temporary decoupling of retail and wholesale prices, but further analysis would be required to confirm these mechanisms.

The ECT between retail and farmgate prices, on the other hand, is -0.27 and statistically significant at the 1% level. This indicates rapid adjustments in this segment, with deviations being corrected within approximately 2.51 weeks. This responsiveness may reflect the priority placed on stabilizing upstream supply chains during the crisis. Wholesalers, dealing directly with production disruptions caused by the fertilizer ban and reduced yields, likely realigned pricing and procurement strategies aggressively to ensure continued supply. The wholesale–farmgate relationship, unlike the retail market, is often characterized by more direct and immediate interactions, such as contractual arrangements or advance purchase agreements, which enable faster adjustments to shocks. The coexistence of these differing ECTs (-0.27, 0.00) and adjustment speeds across the supply chain reflects the varied experiences of each market segment during the crisis. Structural differences play a significant role, as wholesalers often interact directly with producers, while retailers rely on multiple intermediaries, creating delays and inefficiencies. Market priorities also differ: wholesalers may prioritize upstream stability (e.g., securing farmgate supplies) to maintain long-term operations, whereas retailers face unpredictable consumer behaviour and demand-side pressures. Finally, frictions and disruptions disproportionately affected the wholesale–retail link due to its dependence on logistics and consumer trends, while the wholesale–farmgate relationship experienced less downstream volatility and was more responsive. These dynamics highlight the uneven impacts of external shocks along the supply chain and underscore the distinct mechanisms driving price transmission across different market levels.

Table 21: Recovery Period VECM (December 2022 December 2023)

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	0.73***	-0.34	2
Retail – Farmgate	0.30***	-0.24***	2.8
Wholesale – Farmgate	0.41***	-0.37***	1.8

Let us now focus on the period spanning from November 2022 to the end of 2023. During this time, rice prices in Sri Lanka remained elevated, although the inflation rate began to decelerate. Examining the Long-Run Coefficients (LRCs), we observe that all three coefficients are statistically significant at the 1% level. However, their magnitudes are critically low compared to earlier periods, signalling weaker price transmission across market levels. The LRC of 0.73 for the retail–wholesale pair indicates that only 73% of wholesale price changes are transmitted to retail prices over the long run, a significant decline from the COVID period (LRC = 1.01). This suggests that downstream integration between wholesale and retail markets has weakened, possibly due to post-crisis structural inefficiencies or persistent pricing distortions at the retail level. The LRC of 0.30 for the retail–farmgate pair is strikingly low, reflecting that only 30% of farmgate price changes are transmitted to retail prices in the long run. This weak upstream integration likely reflects the lasting effects of supply chain disruptions and structural fragmentation that persisted into the recovery phase. Retail markets may still be decoupled from farmgate prices due to lingering logistical inefficiencies and market distortions. The LRC of 0.41 for the wholesale–farmgate pair similarly highlights weak integration, with only 41% of farmgate price changes reflected in wholesale prices. This could result from the erosion of direct linkages between farmers and wholesalers during the crisis, coupled with inefficiencies in procurement systems that have yet to recover fully.

Turning to the Error Correction Terms (ECTs), we first consider the retail–wholesale pair. The ECT of -0.34 suggests a potentially fast adjustment speed, with a half-life of approximately two weeks. However, it is not statistically significant, meaning there is insufficient evidence to conclude that retail and wholesale prices systematically correct short-run deviations from their long-run equilibrium. While the magnitude of the ECT implies responsiveness, its lack of significance indicates that these adjustments are likely inconsistent or sporadic. This may reflect residual market frictions or inefficiencies in retail–wholesale price transmission, where price shocks are not consistently absorbed. The transitional nature of the recovery period may also contribute to this result, as supply chains stabilize unevenly. Additionally, the shorter timeframe of the recovery period introduces volatility into the dataset, potentially obscuring systematic correction patterns. Thus, the non-significant ECT highlights ongoing challenges in achieving stable short-run price transmission during this phase. In contrast, the ECT for the retail–farmgate pair is statistically significant at the 1% level, increasing to -0.24 compared to -0.10 during the COVID and shock period. This indicates an improvement in short-term responsiveness, with deviations corrected within approximately 2.8 weeks. This suggests that, although the structural linkage between these markets has weakened, there is active responsiveness to short-term disequilibria, likely driven by recovering supply chain efficiency and more direct interactions between retailers and producers.

Similarly, the ECT for the wholesale–farmgate pair is statistically significant at the 1% level and increases to -0.37, indicating that 37% of deviations from equilibrium are corrected within one week, the fastest adjustment observed among all market pairs. This underscores wholesalers' efforts to prioritize upstream supply stabilization during the recovery phase. Such rapid adjustments likely reflect the urgency to rebuild procurement systems and secure consistent farmgate supplies after prolonged disruptions. In summary, while the recovery period shows improved short-term responsiveness across some market pairs, the critically low LRCs indicate that structural integration remains weak. The coexistence of low long-run coefficients with strong error correction terms reflects a market that is dynamically addressing short-term imbalances but still struggling with the deeper structural inefficiencies left in the wake of the crisis.

Table 22: VECM 2019

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	0.98***	-0.54**	0.89
Retail – Farmgate	0.96***	-0.05***	13.51
Wholesale – Farmgate	0.87***	-0.07**	9.55

Let us now focus on 2019 as we further disaggregate the VECM analysis to identify the specific year driving the results. The year 2019 constitutes the larger part of the pre shock period, which spans 2019 and the first two months of 2020.Examining the long-run coefficients, we observe that they are higher than those for the overall recovery period and are closer to unity, indicating stronger long-term market integration.

Turning to the Error Correction Terms (ECTs), we note that the disparity in adjustment magnitudes persists. Specifically, the adjustment speed between retail and wholesale prices is remarkably fast, with approximately 54% of deviations corrected within a week. In contrast, the adjustment speeds between retail and farmgate prices as well as between wholesale and farmgate prices are notably slower, reflecting weaker short-term price transmission in these relationships.

Table 23: VECM 2020

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	1.49***	-0.01	68.62
Retail – Farmgate	1.54***	-0.02**	34.31
Wholesale – Farmgate	0.52***	-0.35***	1.61

Now let us focus on the year 2020. From March onward, this year falls within the COVID and shock subperiod. However, by further disaggregating, we can observe the effect of the pandemic alone on price transmission without capturing the impact of the price shock.

Looking at the long-run coefficients, which, as a reminder, can be interpreted as long-run elasticities, we note that there is over-transmission between retail and wholesale prices and between retail and farmgate prices, as the coefficients exceed one. In contrast, the long-run coefficient between wholesale and farmgate prices dropped significantly to 0.52, marking a sharp reduction compared to its magnitude in 2019.

Turning to the Error Correction Terms (ECTs), the first notable observation is that the ECT between wholesale and retail prices collapsed to 0.01 and is not statistically significant at any level. This indicates that in 2020, there was virtually no short-term adjustment between wholesale and retail prices. On the other hand, the ECT between retail and farmgate prices is -0.02 and is statistically significant at the 1% level, indicating a weekly adjustment of 2% to shocks between these two markets. Finally, despite the sharp decline in the long-run coefficient, the ECT between wholesale and farmgate prices is -0.35, reflecting a very fast short-term adjustment.

In summary, 2020 reveals significant disruptions in short-term price adjustments between wholesale and retail markets, a weakening of the long-term relationship between wholesale and farmgate prices, and contrastingly fast short-term adjustments in the latter relationship.

Table 24: VECM 2021

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	1.11***	0.01	69.31
Retail – Farmgate	0.75***	-0.14**	4.60
Wholesale – Farmgate	0.77***	-0.40***	1.36

Now let us focus on 2021. Examining the long-run coefficients, we observe that the coefficient between retail and wholesale prices remains greater than one, indicating over-transmission in this segment of the value chain. In contrast, the long-run coefficients between retail and farmgate prices and between wholesale and farmgate prices fall below one, suggesting a reduction in long-run market integration. This decline occurred during a year still heavily impacted by the COVID-19 pandemic, and further exacerbated in April 2021 by the ban on the import of chemical fertilizers, which disrupted agricultural production.

Turning to the Error Correction Terms (ECTs), we first examine the relationship between retail and wholesale prices. Here, we again find that the ECT is virtually zero and not statistically significant, indicating a lack of short-term adjustment between these two markets. This trend mirrors what we observed in 2020, where the ECT was similarly close to zero and insignificant. Notably, this lack of short-term adjustment is also consistent with the findings from the three subperiod analyses discussed earlier. Focusing on the ECT between retail and farmgate prices, we observe a marked improvement in the speed of adjustment compared to 2020. The weekly adjustment rate increased to 14%, suggesting that short-term price corrections in this segment of the value chain became faster and more responsive. Finally, the ECT between wholesale and farmgate prices, which was already high in 2020, further increased in 2021, reaching -0.40. This value reflects an exceptionally fast short-term adjustment between these two markets, indicating that wholesale prices quickly responded to deviations from equilibrium in the farmgate market. In summary, while long-run market integration weakened between farmgate markets and both wholesale and retail levels, the short-term adjustment processes varied significantly. The absence of short-term adjustment between retail and wholesale prices persisted, while the farmgate-wholesale relationship exhibited a robust and increasingly rapid short-term correction.

Table 25: VECM 2022

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	0.92***	-1.22***	-
Retail – Farmgate	0.46***	-0.05	13.51
Wholesale – Farmgate	0.49***	-0.07**	9.55

Now let us focus on 2022, a year marked by peak rice and overall food prices, coinciding with severe economic turmoil in Sri Lanka, including economic collapse, power and fuel shortages, and worsening food security. Examining the long-run coefficients, we observe that the coefficient between wholesale and retail prices is no longer greater than one but remains close to unity, indicating a high degree of long-term integration despite the economic instability. In contrast, the long-run coefficients for both retail-farmgate and wholesale-farmgate prices dropped sharply to below 0.5, suggesting a significant breakdown in long-term integration within these segments of the value chain. This deterioration is likely due to severe disruptions in agricultural production, rising input costs, and weakened supply chain connectivity. Turning to the Error Correction Terms (ECTs), we find an exceptional result in the wholesale-retail price relationship. The ECT is -1.22, which is not only statistically significant but also indicates an over-corrective adjustment, meaning that 122% of any disequilibrium between wholesale and retail prices is corrected within one week. Such a rapid and over-corrective adjustment reflects the extreme market pressure and price realignment dynamics driven by maximum price shocks, volatility, and widespread supply chain disruptions caused by fuel shortages and input price spikes. Retail markets likely reacted aggressively to wholesale price changes to restore equilibrium in an environment marked by heightened uncertainty and instability. In contrast, the ECT between retail and farmgate prices is small and not statistically significant, indicating a lack of short-term adjustment in this segment of the supply chain, likely due to inefficiencies and disruptions in agricultural production and distribution. Finally, the ECT between wholesale and farmgate prices is statistically significant at the 1% level and indicates a weekly adjustment of 7%, reflecting a relatively stable short-term correction mechanism between these two markets despite the broader economic turmoil. Overall, 2022 highlights the divergent dynamics within the value chain, with the wholesale-retail relationship showing aggressive short-term corrections while the farmgate-retail segment exhibited clear inefficiencies and stagnation.

Table 26: VECM 2023

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	0.71***	-0.62***	0.716
Retail – Farmgate	0.29***	-0.32***	1.735
Wholesale – Farmgate	0.40***	-0.43***	1.233

Now let us focus on 2023 a year in which rice prices, and food prices in general, remained high but in which the inflation rate slowed down and the economic situation started to slowing improve. This period almost completely overlap from what above we called maybe optimistically recovery period. Looking at the table we can see that in this year the long run coefficients decreased significantly in all the segments of the value chain while the ECTs increased significantly.

4.2.6. Vertical APT

Now let us focus on the results of the asymmetric transmission analysis. Using the non-linear autoregressive distributed lags (NARDL) model, we are able to isolate the responses of markets to both negative and positive shocks in independent variables. Following the results of the Granger causality test, I treated the retail price as the dependent variable and analysed how it reacts to positive and negative shocks in the wholesale market.

The table presents the asymmetry statistics, revealing a significant difference in the magnitude of response in the long-run coefficients. Specifically, the coefficient for positive shocks is 0.937, while the coefficient for negative shocks is 0.915; both coefficients are statistically significant at the 1% level. This indicates that in the long run, the transmission rate of positive shocks from wholesale prices to retail prices is higher compared to negative shocks. Additionally, the Wald test for symmetry, shown in the lower part of the table, rejects the hypothesis of symmetry in both the short and long run. Therefore, we can conclude that there is evidence of asymmetric price transmission between Nadu wholesale and retail prices in both the short and long run.

Table 27: NARDL wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.937***	448.3	0.000	-0.915***	276.3	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat	p>F		F-stat	p>F	
Ln Wholesale → Ln Retail	3.747*	0.053		5.468**	0.020	

The same results are confirmed also for the farmgate and retail prices indeed the long run coefficient for positive shocks is higher than the one for negative shocks and they are both statistically significant. Once again the Wald test for both short and long – run symmetry is rejected thus, we can conclude that there is asymmetric price transmission also between the farmgate price and the retail price. Several theories can explain the phenomenon of downward price stickiness. One such theory posits that when input prices decrease, the previous output price becomes a natural focal point for oligopolistic sellers. In response to a decrease in costs, a downstream firm may opt not to alter its price until demand conditions change. This variant of the "trigger price" model, initially proposed by Green and Porter (1984), is further discussed in Borenstein et al. (1997). According to this framework, increases in farm prices prompt retail price hikes, whereas retail prices may remain inert following negative farm price shocks. It is important to note, however, that evidence of downward price stickiness should not be immediately interpreted as evidence of imperfectly competitive behaviour. Adjustment costs within a perfectly competitive supply chain can also result in this type of price relationship (Gervais, 2011).

Table 28: NARDL farmgate retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.913***	149.9	0.000	-0.897***	117.3	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Farmgate → Ln Retail	2.893*		0.089	5.693**		0.017

Table 29: NARDL Pre Shock (2019 to February 2020) wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.849***	161.6	0.000	-0.816***	14.11	0.001
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Wholesale → Ln Retail	0.046		0.830	2.614		0.144

The long-run effects for price increases (0.849) and price decreases (-0.816) reflect moderately strong price transmission from wholesale to retail markets during the pre-COVID period. The values suggest that approximately 85% of wholesale price changes, whether increases or decreases, were transmitted to retail prices over the long run. The lack of statistical significance in the asymmetry test indicates that price transmission between wholesale and retail was symmetric. This suggests a well-functioning downstream market where retail prices consistently adjusted to wholesale price changes during a stable period without persistent external shocks or distortions.

Table 30: NARDL Pre Shock (2019 to February 2020) farmgate retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.457**	7.13	0.011	-0.329	1.068	0.308
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat	p>F		F-stat	p>F	
Ln Farmgate → Ln Retail	0.511	0.479		0.102	0.751	

The long-run effect for price increases (0.457) indicates that only 45.7% of farmgate price changes were transmitted to retail prices over the long run, while the transmission of price decreases (-0.329) was even weaker. These values reflect limited upstream integration during the pre-COVID period, likely due to policy-driven insulation of farmgate prices or logistical inefficiencies that slowed price adjustments. The non-significant asymmetry test confirms symmetric price transmission, despite the relatively low magnitudes. This suggests that price adjustments from farmgate to retail were stable but weak, highlighting structural inefficiencies in the supply chain rather than opportunistic pricing behaviour.

Table 31: NARDL COVID and Shock (March 2020 to November 2022) wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.919***	1221	0.000	-0.826***	258.1	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat	p>F		F-stat	p>F	
Ln Wholesale → Ln Retail	12.38***	0.001		40.16***	0.000	

The long-run effects for price increases (0.919) and decreases (-0.826) reflect exceptionally strong downstream price transmission during the crisis, with retail prices closely tracking wholesale prices over the long run. However, the transmission of positive wholesale price shocks to retail prices is notably stronger than that of negative shocks. The asymmetry tests indicate that symmetry can be rejected both in the long and short run. This provides robust evidence of positive asymmetric price transmission (APT) between wholesale and retail rice prices during the period from March 2020, when the COVID-19 pandemic began affecting Sri Lanka, to November 2022, when rice prices peaked. The presence of APT in both the short and long run suggests that consumers disproportionately bore the burden of price adjustments, facing faster and greater price increases compared to decreases. This inefficiency, evident in both the speed and magnitude of adjustment, imposed additional strain on households during a period marked by severe food security challenges and heightened economic vulnerability.

Table 32: NARDL COVID and Shock (March 2020 to November 2022) wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.878***	87.22	0.000	-0.828***	27.44	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat	p>F		F-stat	p>F	
Ln Farmgate → Ln Retail	0.562	0.455		5.6**	0.019	

The long-run effects for price increases (0.878) and decreases (-0.828) also indicate strong upstream price transmission during the COVID-19 and the shock period. Farmgate price changes were closely linked to retail prices, with approximately 87.6% of increases and 82.8% of decreases passed through over the long run. This time, the asymmetry tests indicate that symmetry can be rejected only in the short run. This provides robust evidence of positive asymmetric price transmission (APT) between farmgate and retail rice prices during the period from March 2020, when the COVID-19 pandemic began affecting Sri Lanka, to November 2022, when rice prices peaked. However, APT is detected only in the short run indicating that this inefficiency is related only to the speed of price adjustment and thus, the transfer of welfare is only temporary.

Table 33: NARDL Recovery Period (December 2022 December 2023) wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.736***	2505	0.000	-0.777***	26.61	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat	p>F		F-stat	p>F	
Ln Wholesale → Ln Retail	10.02***	0.003		2.33*	0.08	

The long-run coefficient for price increases (0.736; significant) and price decreases (-0.777; significant) suggests moderate long-term price transmission during the recovery period. The values indicate that approximately 73.6% of wholesale price increases and 77.7% of price decreases were transmitted to retail prices over the long run. Compared to the earlier periods, the transmission weakened, reflecting a potential stabilization in retail price adjustments after the extreme volatility of the COVID and shock period. Long-run asymmetry is statistically significant (F-stat: 10.02, p < 0.01), indicating that price transmission was asymmetric. Notably, the asymmetry reflects a pattern where retail prices fell more sharply than they rose in response to wholesale price changes. This negative asymmetry suggests that retailers passed cost reductions more fully to consumers than cost increases, possibly driven by consumer demand recovery, competitive pressures, or reduced input costs during the stabilization phase. Short-run asymmetry is marginally significant (F-stat: 2.33, p = 0.08), indicating some evidence of differences in the speed of adjustment between price increases and decreases. However, the weaker statistical significance suggests that the asymmetry in short-run dynamics was less pronounced than in earlier periods.

Table 34: NARDL Recovery Period (December 2022 December 2023) wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.319***	511	0.000	-0.311	392.9	0.000
	Long Run asymmetry			Short Run asymmetry		
	F-stat	p>F		F-stat	p>F	
Ln Farmgate → Ln Retail	0.9	0.757		0.10	0.752	

The long-run coefficients between the retail and farmgate prices dropped significantly during the recovery period mimicking the behaviour of the long run coefficients of the VECM. However looking at the asymmetry statistics we notice that during this time period the adjustment process between farmgate and retail prices is symmetric both in the long and in the short run.

Table 35: NARDL 2019 wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.934***	549.3	0.000	-1.022	61.79	0.000
	Long Run asymmetry			Short Run asymmetry		
	F-stat	p>F		F-stat	p>F	
Ln Wholesale → Ln Retail	0.7656	0.387		0.081	0.770	

Table 36: NARDL 2019 farmgate retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.644**	7.439	0.010	-0.739	1.518	0.225
	Long Run asymmetry			Short Run asymmetry		
	F-stat	p>F		F-stat	p>F	
Ln Farmgate → Ln Retail	0.051	0.821		0.027	0.870	

I will now analyse the results of the NARDL model year by year, with the objective of further disaggregating the APT results to identify the specific years driving the observed outcomes. Focusing on the results for 2019, we observe a counterintuitive finding for both the wholesale-retail and farmgate-retail market pairs. Specifically, the long-run coefficients for negative shocks in the Granger-causing markets are greater than those for positive shocks. However, as shown in the two tables, we cannot reject any of the symmetry tests. This indicates that, in 2019, the price transmission process was symmetric.

Table 37: NARDL 2020 wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	1.589***	9.947	0.000	-1.382**	6.312	0.01
	Long Run asymmetry			Short Run asymmetry		
	F-stat	p>F		F-stat	p>F	
Ln Wholesale → Ln Retail	1.106	0.299		0.524	0.470	

Table 38: NARDL 2020 farmgate retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.799	2.22	0.144	-0.556	1.159	0.280
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Farmgate → Ln Retail	1.415		0.241	2.381		0.131

Examining the results for 2020, we observe that, as anticipated, the long-run coefficients for positive shocks are once again higher in absolute value than the long-run coefficients for negative shocks. Additionally, for the wholesale-retail market pairs, the coefficients exceed unity, indicating an over-transmission of both positive and negative shocks from the wholesale level to the retail level. However, we are unable to reject the symmetry tests, and thus, there is no evidence of asymmetric price transmission (APT). This suggests that the significant APT identified during the COVID and SHOCK period was not solely driven by the events of 2020.

Table 39: NARDL 2021 wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.879***	146.4	0.000	-0.829***	63.17	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Wholesale → Ln Retail	1.741		0.195	30.01		0.000

Table 40: NARDL 2021 farmgate retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	1.069	2.131	0.1520	-1.488	1.05	0.312
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Farmgate → Ln Retail	0.321		0.574	4.976**		0.032

Turning our attention to the results for 2021, we begin with the wholesale-retail market pair. The long-run coefficients show a significant decrease compared to the previous year, falling below one but remaining relatively high, reflecting a sufficient level of market integration. The long-run coefficient for positive shocks (0.879) is higher than that for negative shocks (0.829). Notably, the symmetry tests reveal that we can strongly reject short-run symmetry, indicating the presence of positive asymmetric price transmission (APT) between wholesale and retail prices in 2021.

In the case of the farmgate-retail market pair, the long-run coefficients remain above one. Interestingly, the coefficient for negative shocks exceeds that for positive shocks. This finding, combined with the rejection of the short-run symmetry test, suggests the presence of negative APT. Consequently, in 2021, consumers experienced a temporary welfare transfer from producers.

Table 41: NARDL 2022 wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.955***	16549	0.000	-0.890***	2791	0.000
	Long Run asymmetry			Short Run asymmetry		
	F-stat	p>F		F-stat	p>F	
Ln Wholesale → Ln Retail	28.63***	0.000		3.489*	0.069	

Let us now focus on the year 2022, a period marked by peak rice and overall food prices, coinciding with a year of economic turmoil for Sri Lanka characterized by economic collapse, power and fuel shortages, and worsening food security. Examining the long-run coefficients, we observe that they are close to one, with the coefficient for positive shocks exceeding that for negative shocks.

Importantly, the symmetry tests reveal that we can reject symmetry in both the long and short run. This indicates evidence of positive asymmetric price transmission (APT) between the wholesale and retail levels in both the short and long term. From this further disaggregation of the time periods, it becomes evident that 2022 played a pivotal role in driving the results observed during the COVID and shock period.

Table 42: NARDL 2022 farmgate retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	1.030***	252.9	0.000	-0.751***	78.53	0.000
	Long Run asymmetry			Short Run asymmetry		
	F-stat	p>F		F-stat	p>F	
Ln Farmgate → Ln Retail	33.68***	0.000		4.493**	0.040	

Now turning to the results for the farmgate-retail markets, we observe that the long-run coefficient for positive wholesale shocks remains above one, while the coefficient for negative shocks has sharply declined to 0.751. This indicates that negative shocks in farmgate prices are weakly transmitted to retail prices compared to positive shocks. This asymmetry may be attributed to the sharp increase in paddy prices, driven by a severe reduction in supply caused by a lack of fertilizer and its rising cost. The symmetry tests further reveal that we can reject symmetry in both the long and short run. Thus, we conclude that positive asymmetric price transmission (APT) was also present between farmgate and retail prices in 2022.

Table 43: NARDL 2023 wholesale retail

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.745***	947	0.000	-0.769	334.9	0.000
	Long Run asymmetry			Short Run asymmetry		
	F-stat	p>F		F-stat	p>F	
Ln Wholesale → Ln Retail	0.888	0.352		3.92	0.054	

Let us now focus on the year 2023, a year in which rice prices, and food prices in general, remained high but in which the inflation rate slowed down and the economic situation started to slowing improve. This period almost completely overlap from what above we called maybe optimistically recovery period indeed the result are very similar with a negative APT in the short run between wholesale and retail prices.

Table 44: NARDL 2023 farmgate retail

Exogenous variables	**Long Run effect [+]**			**Long Run effect [-]**		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.306***	145.5	0.000	-0.284***	50.96	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Farmgate → Ln Retail	0.593		0.446	1.01		0.302

Finally looking at the results between farmgate and retail prices we notice that they are very similar to the one of the recovery period with very low long run coefficients and symmetric adjustment process.

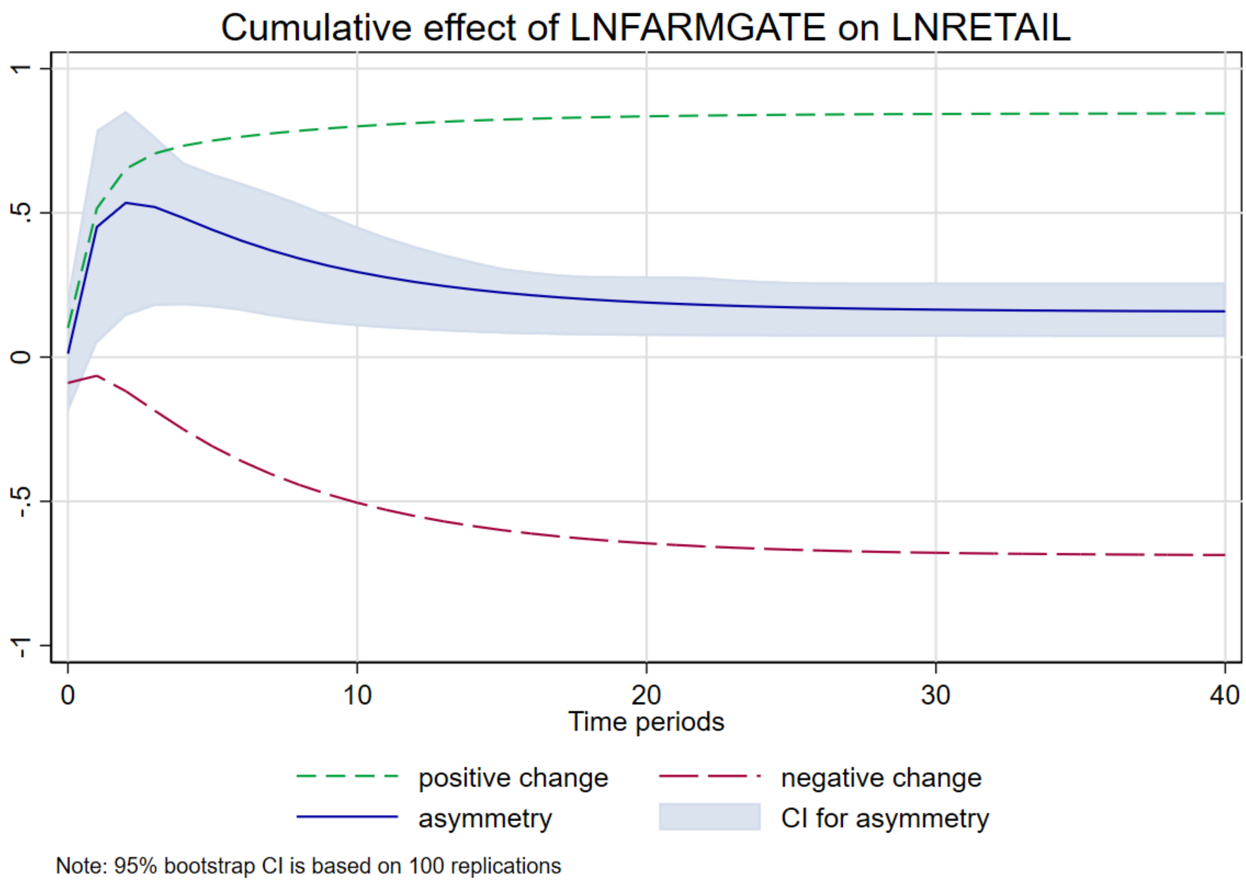

Figure 8: Dynamic multiplier wholesale to retail level

Author's elaboration using HARTI data.

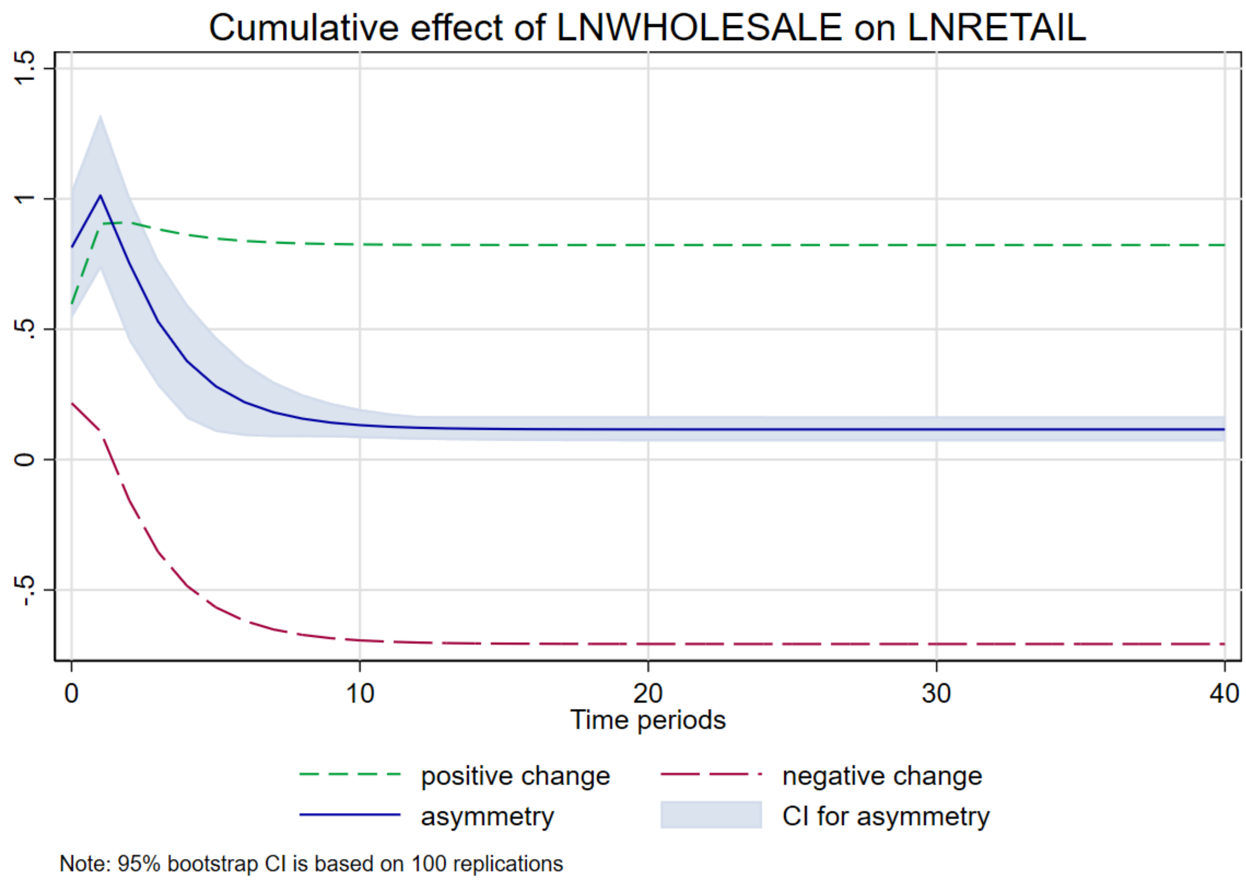

Figure 9: Dynamic multiplier farm to retail level
Author's elaboration using HARTI data.

The figures above illustrate the dynamic multipliers for price transmission from the wholesale to the retail level and from the farmgate to the retail level. Both graphs visually confirm the presence of positive Asymmetric Price Transmission (APT) within the supply chain. Figure 9 demonstrates that the retail price response differs in magnitude between positive and negative shocks to the wholesale price. After ten weeks, the positive asymmetry diminishes but remains above zero in the long run. Similarly, the response of retail prices to farmgate prices shows a less pronounced initial kink, yet it persists over time.

The ensuing tables delineate the Nonlinear Autoregressive Distributed Lag (NARDL) model results for both the Maha and Yala seasons. Table 45 illustrates that the long-run response of retail prices to positive shocks exceeds that to negative shocks, with both coefficients achieving statistical significance at the 1% level. Specifically, within the Maha season, evidence suggests only short-term positive asymmetry, as the null hypothesis of symmetry remains unchallenged in the Wald test, indicating that the welfare transfer from consumers to wholesalers is transient. Conversely, Table 46 outlines the NARDL outcomes for the Maha season between farmgate and retail prices, where long-run coefficients remain significantly impactful at 1%, showing a greater transmission rate for positive shocks from farmgate to retail prices. Yet, symmetry in both the long and short run cannot be dismissed according to the Wald test results. Table 47 highlights the Yala season, where long-run coefficients for the wholesale-retail pair are statistically significant, albeit with a slightly higher coefficient for negative shocks; however, evidence of Asymmetric Price Transmission (APT) remains elusive. Lastly, Table 48 presents the Yala season's NARDL findings between farmgate and retail prices, where the long-run coefficients are significantly distinct at the 1% level, favouring positive shocks. This time, the results from the symmetry Wald test substantiate the presence of positive APT in both the short and long run, indicating a permanent welfare shift.

Table 45: NARDL wholesale retail Maha

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.964***	629.1	0.000	-0.942***	332.5	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Wholesale → Ln Retail	1.921		0.167	3.439*		0.065

Table 46: NARDL farmgate retail Maha

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.965***	91.25	0.000	-0.949***	67.03	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Farmgate → Ln Retail	0.804		0.371	0.026		0.871

Table 47: NARDL wholesale retail Yala

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	1.025***	153.2	0.000	-1.026***	78.74	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Wholesale → Ln Retail	0.001		0.967	1.832		0.177

Table 48: NARDL farmgate retail Yala

Exogenous variables	Long Run effect [+]			Long Run effect [-]		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Farmgate → Ln Retail	0.892***	153.9	0.000	-0.855***	89.95	0.000
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Farmgate → Ln Retail	2.952*		0.087	5.515**		0.020

5. Conclusions

This study analysed the spatial and vertical integration of Nadu rice in Sri Lanka and assessed the presence of Asymmetric Price Transmission (APT) within the vertical supply chain. Regarding spatial integration, our results indicate that the price series in the ten selected locations are stationary in first differences, thus integrated of order one, I(1). We observed a high degree of long-term integration among all markets, suggesting efficient spatial price movement for Nadu rice. Granger causality tests between two central markets (Colombo and Gampaha) and regional markets revealed mostly bidirectional relationships, indicating no clear market dominance in rice price formation, except for Trincomalee, which is influenced by Colombo central markets. Furthermore, the speed of price adjustment was higher for regional markets compared to central markets, with distance playing a significant role in determining adjustment speed.

In the vertical analysis of farmgate, wholesale, and retail prices, we found that all three price series are integrated of order one, I(1), and exhibit long-term integration. The Granger causality test reveals that price formation primarily occurs at the upstream level of the supply chain. All pairs of prices exhibit unidirectional causality, with farmgate prices Granger-causing both retail and wholesale prices, and wholesale prices, in turn, unidirectionally causing retail prices. The highest speed of adjustment was observed between wholesale and retail levels of the supply chain, while the slowest adjustment was observed between farmgate and wholesale with an ECT of -0.037. This slower adjustment may be attributed to government interventions in the paddy sector, such as ceiling prices on farmgate prices, which contribute to a more rigid adjustment process.

Additionally, we identified positive APT in both the short and long run from wholesale to retail and from farmgate to retail prices. The asymmetry statistics are significant both in the short and in the long run, indicating a permanent welfare transfer. The negative impact of APT in the Sri Lankan rice market ultimately affects consumers that bear the cost of this inefficiency, potentially threatening food security due to rice's central role in the national diet. However, after accounting for seasonality, we found that during the Maha season, there is a positive asymmetric price transmission (APT) between retail and wholesale prices, but only in the short run. In contrast, the price transmission process between farmgate and retail prices is symmetric. Conversely, during the Yala season, no APT is observed between retail and wholesale prices, but there is APT between farmgate and retail prices in both the short and long run. Therefore, controlling for seasonality reveals a diminishing effect on positive APT. The latter highlights the critical importance of accounting for seasonal variations in price transmission studies. This consideration is particularly important when examining perishable crops like fruits and vegetables, although it is relevant for paddy rice as well, especially for economically vulnerable farmers who lack adequate storage facilities. While identifying the exact causes of APT falls beyond the scope of this study, existing literature points to a concentration of market power within the country’s milling sector (Mufeeth et al., 2022; Wijesooriya and Kuruppu, 2022).

To delve deeper into recent price dynamics, the analysis focused on 2019–2023, a period marked by internal and external shocks. These shocks, particularly the 2022 inflationary spiral, were driven by Sri Lanka’s worst economic crisis in decades.

These disruptions destabilized supply chains, worsening price transmission inefficiencies across both spatial and vertical markets and amplifying food insecurity nationwide. Before the shocks, there was moderate long-term integration along the value chain, with fast price adjustments between retail and wholesale prices, and moderate adjustments between farmgate and wholesale as well as farmgate and retail prices. During the shock period (March 2020 to November 2022), long-term integration increased, particularly in the wholesale-retail pair, where the ECT dropped to zero, a result driven primarily by 2020 and 2022. In the recovery period, long-term coefficients declined significantly, but short-term responsiveness improved markedly across all market levels. The NARDL analysis revealed symmetric price transmission in the pre-shock period between wholesale, retail, and farmgate prices. However, during the shock period, especially in 2022, pronounced positive asymmetry emerged, disproportionately affecting consumers.

These findings provide a valuable foundation for policymakers aiming to design more efficient supply chains for Nadu rice. While the Nadu supply chain demonstrates a high level of integration, our analysis reveals inefficiencies that vary between the two agricultural seasons and may adversely affect consumers. The negative welfare impacts of APT on consumers, especially during price shocks like the one in 2022, emphasize the need for social safety nets. Programs such as cash transfers or food subsidies could provide crucial support to low-income households during periods of high food inflation. The latter is also a call to develop a national-level early warning system to track key food and nutrition security indicators, enabling proactive policy interventions and flexible response programming. Such a system would be particularly valuable during high-price periods, enhancing resilience and ensuring a more stable and secure food supply for the population.

Enhancing the efficiency of the Nadu supply chain appears to hinge on increasing the competitiveness of the milling sector and bolstering the bargaining power of smallholders. This could be achieved by strengthening farmers' organizations and establishing cooperatives and applying antitrust laws in the milling and retail sector to avoid formal or informal lobbies. Additionally, the literature indicates that farmgate prices tend to plummet during peak harvesting seasons. To address this, the government could incentivize the development of storage facilities, enabling farmers to reduce the urgency to sell and negotiate better prices. Furthermore, the seasonal variation in price transmission call for measures such as buffer stock mechanisms during peak harvest periods, to stabilize prices and prevent sharp declines. Developing decentralized storage facilities could allow farmers to store surplus rice, reducing pressure to sell immediately after harvest when prices are low, thereby smoothing out seasonal price fluctuations. Furthermore, the government could address inefficiencies in the PMB's system by increasing storage capacity, streamlining procurement processes to ensure timely purchases at guaranteed prices, and improving stock release mechanisms to prevent retail price surges during crises. Integrate advanced market information systems to anticipate trends, align interventions with price fluctuations, and improve responsiveness during shocks.

The presence of positive Asymmetric Price Transmission (APT) in Nadu retail prices creates opportunities for further research. A critical area of investigation should be the quantification of consumer welfare losses resulting from this inefficiency, as well as its interaction with producer welfare. In the context of a country like Sri Lanka, where there may be significant overlap between consumer and producer interests, this relationship warrants careful examination. Another critical unanswered question is why this phenomenon occurs within the Nadu supply chain. Addressing this question requires a thorough investigation of the market structure and the milling sector. However, this analysis necessitates the collection of new data, as the last comprehensive rice milling survey was conducted in 2006, making the existing data less relevant for current conditions. Finally, considering the recent price shock that hit the country leading to soaring food inflation a key area of inquiry will be to understand how such price shocks and broader price dynamics influence the productive and diversification strategies of paddy farmers and their food security.

Thus, Future research should focus on how the 2022 price shock affected paddy-producing households, particularly in terms of their food security and productive strategies, such as diversification. Building on the findings of this study, it is important to explore how rice price shocks influence households' decisions to diversify into other crops and how farm diversification serves as a buffer against food insecurity. Using Propensity Score Matching (PSM) to address the endogeneity of diversification, along with Generalized Propensity Score (GPS) to assess the impact of varying price shock intensities, future studies could provide deeper insights into the role of diversification in mitigating the negative effects of price shocks on FIES and HDDS outcomes. This research would offer crucial policy recommendations for promoting diversified farming systems to enhance household resilience and food security in Sri Lanka’s rice-producing regions.

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