

Analysis of spatial Integration of Bean Markets prices in South Kivu, North Kivu, and Tanganyika, DRC: A Cointegration Approach

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ABSTRACT

Bean markets in the provinces of South Kivu, North Kivu, and Tanganyika in the Democratic Republic of Congo face significant challenges, including rising prices and inefficiencies in market integration. The price of beans has more than tripled in recent years, exacerbating food insecurity and economic vulnerability. However, limited empirical research has explored the spatial integration of these markets, despite its importance for policy interventions. This study analyzes the degree of market integration using monthly retail price data from 2017 to 2024 sourced from the National Agricultural Statistics Service. The analysis employs cointegration techniques, including the Augmented Dickey-Fuller test, Error Correction Models (ECM), and the Market Connection Index (MCI). The findings reveal that the markets are long-term integrated, with an average of 32% of price deviations corrected monthly. Among the seven market pairs tested, faster adjustments are observed in markets like Rutshuru-Goma (37%), while slower adjustments are seen in more remote markets such as Moba-Kalemie and Uvira-Bukavu (26% and 27%). These variations in market integration highlight the role of geographic and infrastructural factors. The study recommends targeted interventions, including investments in transport infrastructure, strengthening Market Information Systems (MIS), and supporting local producers, to reduce price volatility and improve food security in the region. Future research could build on this study by using higher-frequency data, such as weekly prices, to capture more detailed market dynamics.

KEYWORDS: Bean markets, spatial integration, price transmission, cointegration, food security.

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1. INTRODUCTION

Common bean (*Phaseolus vulgaris*) is an essential legume, cultivated, consumed and traded globally. It plays a vital role in food security and income generation, particularly in sub-Saharan Africa where it supports the livelihoods of millions of farming households (Boaz et al., 2022; Nchanji et al., 2021). Benavides et al. (2021) support that common bean is a critical grain legume for direct human consumption and serves as a staple crop for many rural communities in tropical regions, especially in East and Southern Africa. It is estimated that more than 300 million people in tropical regions include beans in their daily diets (Lisciani et al., 2024). Although beans have traditionally been a subsistence crop, it has increasingly become a major cash crop, with a growing market (Boaz et al., 2022). In the Democratic Republic of Congo (DRC), beans are recognized as a priority crop due to their substantial benefits for rural households (Jandrain & Frison, 2022).

However, the past two decades have seen a dramatic rise in bean prices on DRC markets. Notably, the average price of a ton of beans rose from approximately USD 48 in 2019 to USD 123 in 2024, an increase of more than 200% (FAO, 2025). This price inflation has severe implications for vulnerable populations, both urban and rural, whose purchasing power is increasingly eroded.

Given that approximately 49% of the Congolese population lives below the poverty line (FAO, 2022), such price hikes could exacerbate extreme poverty for millions of people living on less than a dollar a day.

Such price increase may also signal inefficiencies within the food distribution system between surplus production areas and deficit consumption areas. Ineffective spatial integration of agricultural markets means that price signals are not efficiently transmitted. This situation is exhibited when surplus regions fail to benefit producers with better prices, while deficit regions struggle with insufficient and unaffordable supplies. This lack of market integration can lead to speculation and heightened price volatility. The effectiveness of food markets in linking production and consumption zones determines whether supply meets demand affordably and efficiently. As Ihle, Amikuzuno, and Cramon-Taubadel (2010) note, the success of any intervention to improve food access hinges on the timely and accurate transmission of price and demand signals across geographic spaces.

Despite the significance of these issues, limited empirical studies have specifically examined the integration of bean markets in the provinces of South Kivu, North Kivu, and Tanganyika. In addition, insecurity in these regions, logistical difficulties, and a lack of data on the economic efficiency of agricultural value chains (Templer et al., 2022), further hinder a comprehensive understanding of the situation. Although, understanding the dynamics of the bean value chain, specifically how beans move from surplus to deficit areas, the degree of market integration, and the factors influencing these movements, is crucial for designing effective policies and programs aimed at improving food security and alleviating poverty

Therefore, the study sought to fill this knowledge gap by assessing the spatial market integration of the bean value chain in the provinces of South Kivu, North Kivu, and Tanganyika in DRC. The objective was to analyze how markets function to move beans from surplus to deficit areas, to measure the degree of integration between key markets, and to identify factors contributing to the observed dynamics. Such an understanding helps in identifying strategies to improve market efficiency, reduce price volatility, and ultimately improve food security and the well-being of populations in these provinces.

2. THEORETICAL FRAMEWORK

This study is grounded on the Law of One Price (LOOP), which posits that in perfectly integrated markets, the prices of a homogeneous good should be identical across different locations once adjusted for exchange rates and transport costs (Guesmi Khaled, Nguyen Duc Khuong, 2011). When markets are integrated, a price shock in one market is expected to be transmitted to other interconnected markets, indicating an interdependence in price movements across space (Fousseini & Diop, 2021). However, when price disparities exceed the bounds of transaction costs, it implies that markets are segmented rather than integrated. This segmentation may arise due to a range of frictions including high transport costs, poor infrastructure, information asymmetry, trade barriers, or imperfect competition (Barrett, 2001; Timmer, 2009). These factors inhibit spatial arbitrage and reduce the efficiency of price transmission, affecting both producers and consumers.

3. BRIEF LITERATURE REVIEW

Empirical studies on spatial market integration have evolved significantly, transitioning from basic analytical tools to more advanced econometric approaches. Previous research primarily relied on bivariate correlations and simple regression models, which proved insufficient for capturing causal relationships and controlling for confounding factors (Kmenta, 2015). These limitations were also widely acknowledged by Barrett (1996), who advocated for more robust techniques capable of capturing the complex dynamics of price transmission. This led to the adoption of cointegration analysis and error correction models (ECMs), which not only assess long-term equilibrium relationships between markets but also track short-term price adjustments (Amikuzuno & Ogundari, 2015; Baidya & Maity, 2023). These models have become central to integration studies, offering stronger insights into market behavior over time. However, they often depend on high-frequency and high-quality data which is not always available.

To address the non-linear nature of price transmission, Threshold Autoregressive (TAR) models were introduced, offering a more refined lens that accounts for market frictions and asymmetric adjustments due to transaction costs (Ling et al., 2015). While these methods are methodologically superior, TAR models are data intensive, limiting their practical use in contexts where price data is often sparse, irregular, or inconsistently recorded (Amankwah-Amoah et al., 2018). Particularly, in the Sub-Saharan African context, empirical evidence on market integration remains limited. Notable contributions by Mumbeya (2011) have demonstrated the utility of cointegration and ECM techniques even when data quality is suboptimal. However, as highlighted in a meta-regression by Amikuzuno & Ogundari (2015), there remains substantial heterogeneity in price transmission estimates across studies. This inconsistency reflects both methodological variation and context-specific challenges.

To address these challenges, this study adopts a pragmatic yet robust econometric strategy. Given the availability of monthly price series, the analysis will employ the cointegration technique and the Error Correction Model (ECM) to assess long-run relationships and short-term adjustment dynamics. Additionally, the Market Connection Index (MCI) will be used to provide further insight into short-term price linkages. This combination offers a balanced methodological approach that is suitable for the context while responding directly to gaps identified in existing empirical work.

4. METHODOLOGY

4.1. Study area

The study focused on the three provinces in the DRC: South Kivu, North Kivu, and Tanganyika. These provinces were selected because of their importance as key intervention areas for agricultural development projects focused on bean cultivation and women's empowerment, such as the B4WE project. Geographically, the study areas spans between 1°36' and 5° South latitude, and 26°47' and 29°20' East longitude, covering a total area of approximately 69,130 km². The region is known for its diverse agricultural production, including crops such as sorghum, beans, potatoes, sweet potatoes, maize, cassava, bananas. However, the area faces considerable challenges related to security and infrastructure. Agricultural research centers and stations such as the National Institute for Agricultural Studies and Research (INERA) are present in the region, providing valuable resources and research on agricultural practices. These centers play a key role in shaping local agricultural strategies and fostering innovation, making them crucial for understanding the agricultural dynamics in the study area. For this study, 10 representative markets were selected in these three provinces including Bukavu, Goma, Kalemie, Masisi, Moba, Mudaka, Mugogo, Rutshuru, Tabac, Uvira.

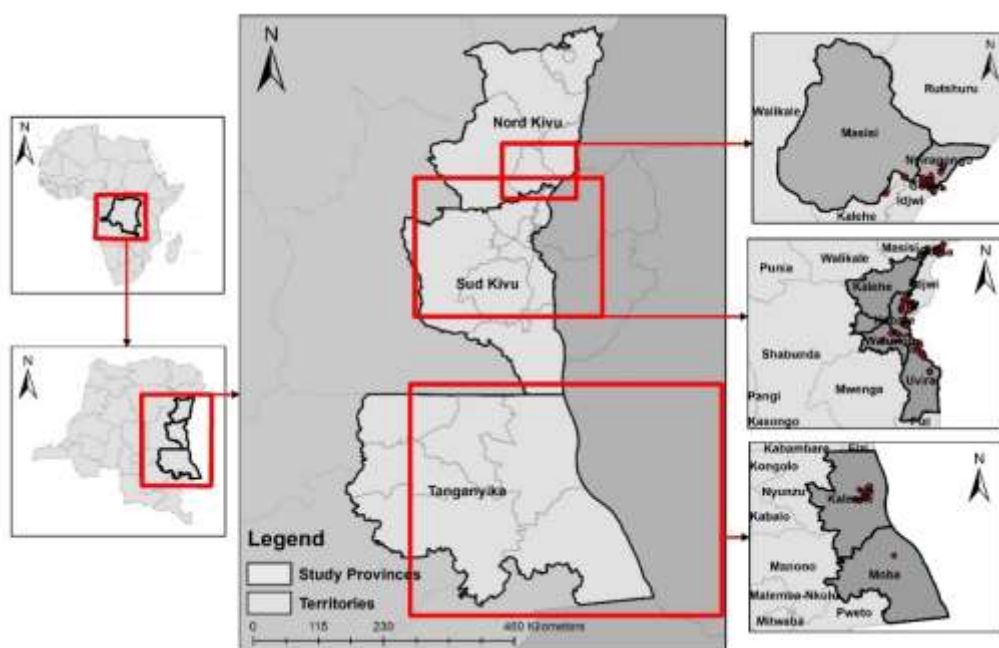


Figure 1: Study Area

4.2. Data type and Source

The study utilized secondary time series data on monthly retail bean prices from January 2017 to November 2024. The data was sourced from the National Agricultural Statistics Service database of the provinces of North Kivu, South Kivu and Tanganyika. To correct for potential heteroskedasticity and ensure comparability across time, the price series were transformed using natural logarithms. This transformation also enables model coefficients to be interpreted as percentage changes, which enhances the economic interpretability of the results. Where applicable, missing data points were handled using linear interpolation to maintain continuity in the series without introducing bias.

4.3. Analytical Framework

4.3.1. Unit Root Dependency Test

Before testing for cointegration, it is necessary to determine the order of integration of individual price series. The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) is used for this purpose. The test evaluates the null hypothesis (H_0) that a series has a unit root (non-stationary) against the alternative hypothesis (H_1) that it is stationary around a deterministic trend. The estimated ADF regression is:

$$\Delta Y_t = \alpha + \beta t + (\rho - 1)Y_{t-1} + \sum_i \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

where Δ is the first difference operator, Y_t is the logarithm of the price at time t , α is a constant, βt represents a time trend, ρ is the autoregressive coefficient, and the terms ΔY_{t-i} capture the short-term dynamics. The number of lags (p) is determined using the Schwarz information criterion (SIC).

If the null hypothesis ($\rho - 1 = 0$) cannot be rejected for the level series but is rejected for the first difference series, the series is integrated of order 1, denoted as $I(1)$.

4.3.2. Cointegration and Error Correction Model (ECM)

Once the price series for two markets (e.g., a local market P_t and a reference market R_t) are confirmed to be $I(1)$, cointegration can be tested to assess whether a long-run equilibrium relationship exists between the two series. The long-run relationship is given by:

$$P_{it} = \beta_0 + \beta_1 R_{jt} + \varepsilon_t \quad (2)$$

where ε_t is the error term that represents the deviation from equilibrium. If ε_t is stationary ($I(0)$), then the series are cointegrated. The Error Correction Model (ECM) (Engle & Granger, 1987), based on the Granger representation theorem, combines both short-run and long-run dynamics. The model is specified as:

$$\Delta P_{it} = d_0 + d_1 \varepsilon_{t-1} + d_2 \Delta R_{jt} + d_3 \Delta R_{jt-1} + \dots + d_4 \Delta P_{it-1} + \gamma X_t + U_t \quad (3)$$

Where $\varepsilon_{t-1} = P_{it-1} - \beta_0 - \beta_1 R_{jt-1}$ is the lagged error correction term, representing the deviation from the previous period's equilibrium. The terms ΔP_{it} and R_{jt} represent the short-term changes in prices, and X_t includes other relevant variables (e.g. seasonality) if available.

Key parameters in the ECM are:

- d_1 : This coefficient measures the speed of adjustment toward long-term equilibrium. A negative and statistically significant d_1 confirms cointegration and error correction. The absolute value of d_1 indicates the percentage of disequilibrium corrected during the current period (month). A value close to -1 suggests rapid adjustment, while a value closer to 0 indicates a slower adjustment. This concept is illustrated in Figure 2, where the system fully corrects back to equilibrium within one period.
- d_2 : This coefficient measures the short-term impact of changes in the reference price on the local price.
- Lagged coefficients (e.g., d_3, d_4): These capture the short-term dynamic effects.

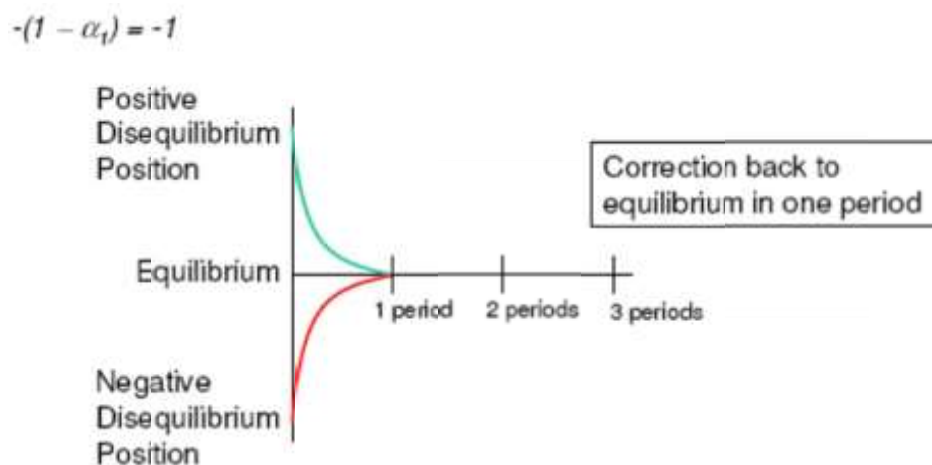


Figure 2: Illustration of the adjustment towards equilibrium

Hypotheses tested in the ECM include:

- Long-run integration: $H_0: d_1 = 0$ (no cointegration/error correction) vs. $H_1: d_1 < 0$ (cointegration and error correction).
- Market segmentation: If d_1, d_2 and other coefficients related to R_j are not significant, this indicates market segmentation.
- Short-term perfect integration: This can be tested by imposing restrictions on the coefficients, such as $d_2 = 1$ and other $d_j = 0$.

4.3.3. Market Connection Index (MCI)

To analyze short-term price transmission, the Market Connection Index (MCI), proposed by Timmer (1986), was employed. This index measures the short-run price transmission elasticity from the reference market to the local market. It is typically estimated from a model derived from the ECM parameters. It is guided by the model in equation 4 below:

$$\Delta P_{it} = \alpha_0 + \alpha_1 \Delta P_{it-1} + \beta_0 \Delta R_{jt} + \beta_1 \Delta R_{jt-1} + \dots + \theta \varepsilon_{t-1} + v_t \quad (4)$$

The MCI can be approximated by β_0 (the immediate impact) or a combination of the short-run coefficients. A high MCI (close to 1) suggests a strong short-run connection between markets, while a low MCI (close to 0) indicates weak transmission of short-term price shocks.

5. RESULTS AND DISCUSSION

5.1. Market Price trends across hubs

The analysis of nominal bean price trends over time reveals key patterns of fluctuation and divergence across markets. As shown in Figure 3a, most markets experienced a general upward trend in nominal prices, with more pronounced volatility emerging between 2021 and 2022. This escalation likely reflects increased market disruptions or seasonal supply-demand mismatches during that period.

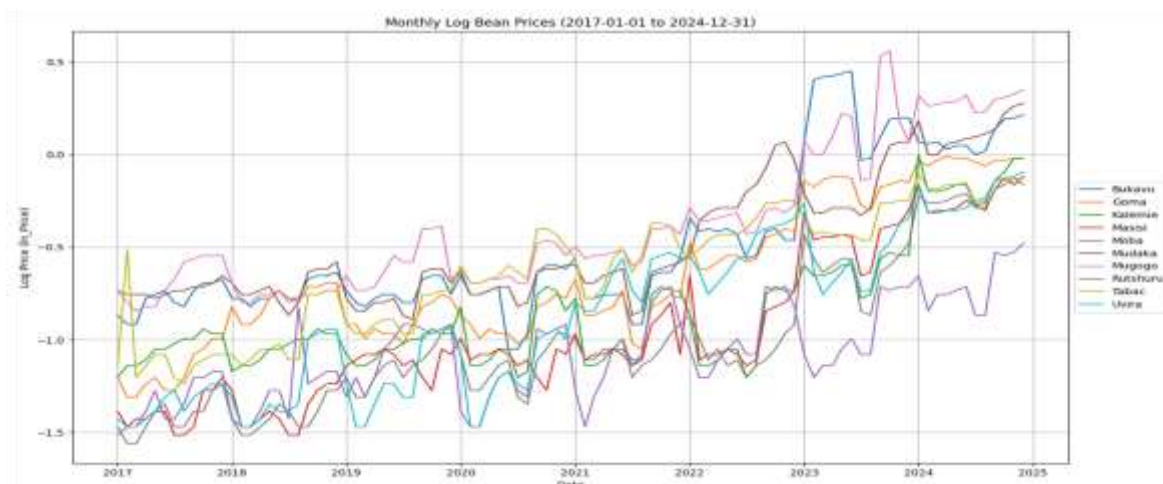
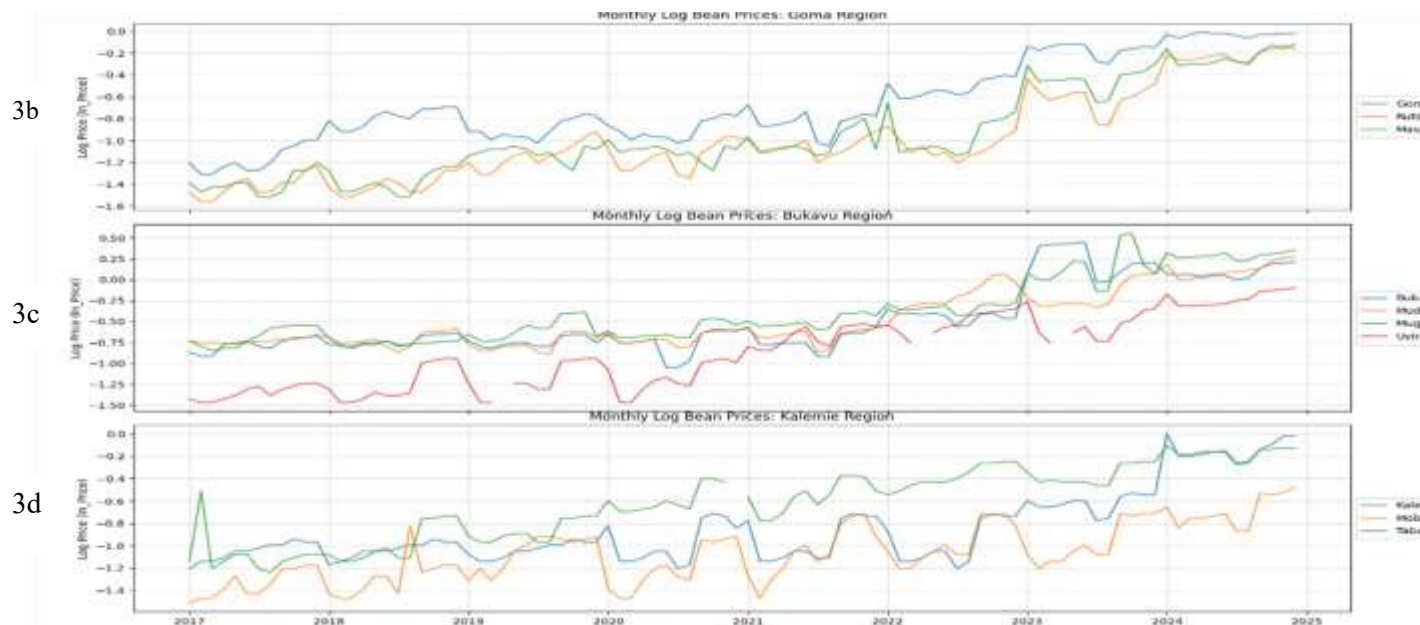


Figure 3a shows a general upward trend in nominal bean prices over the entire period for most markets, with notable volatility and an increase in the upward trend from 2021-2022.

Further regional analysis, presented in Figures 3b, 3c, and 3d, disaggregates price movements by major market hubs: Goma, Bukavu, and Kalemie, respectively. These figures highlight varied price trajectories and volatility levels, suggesting that market responses were not uniform. For instance, while some hubs exhibited sharp price spikes, others reflected steadier but elevated price growth. This regional variation underscores differences in market integration, infrastructure, or regional shocks influencing bean trade.



Figures 3b, 3c and 3d illustrate the specific dynamics within each regional hub (around Goma, Bukavu and Kalemie), showing varying price levels and volatility profiles between markets.

5.2. Marketing Channel and Commodity flow

The analysis reveals a fragmented bean marketing system in eastern DRC, shaped by years of conflict, infrastructure collapse, and limited coordination. As illustrated in figure 4, the trade routes are organized around three major urban centers of Goma, Bukavu and Kalemie. Goma is majorly supplied by Masisi and Rutshuru. Bukavu draws beans from Mudaka, Mugogo, and Uvira while Kalemie sources its supply from Moba and Tabac. These cities also serve as key hubs for bean imports from Rwanda, Burundi,

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Uganda, and Tanzania, reflecting the declining self-sufficiency of local production systems. Once surplus-producing regions, these provinces are now increasingly reliant on cross-border trade due to prolonged insecurity, limited input access, and poor infrastructure (NAAS, 2024).

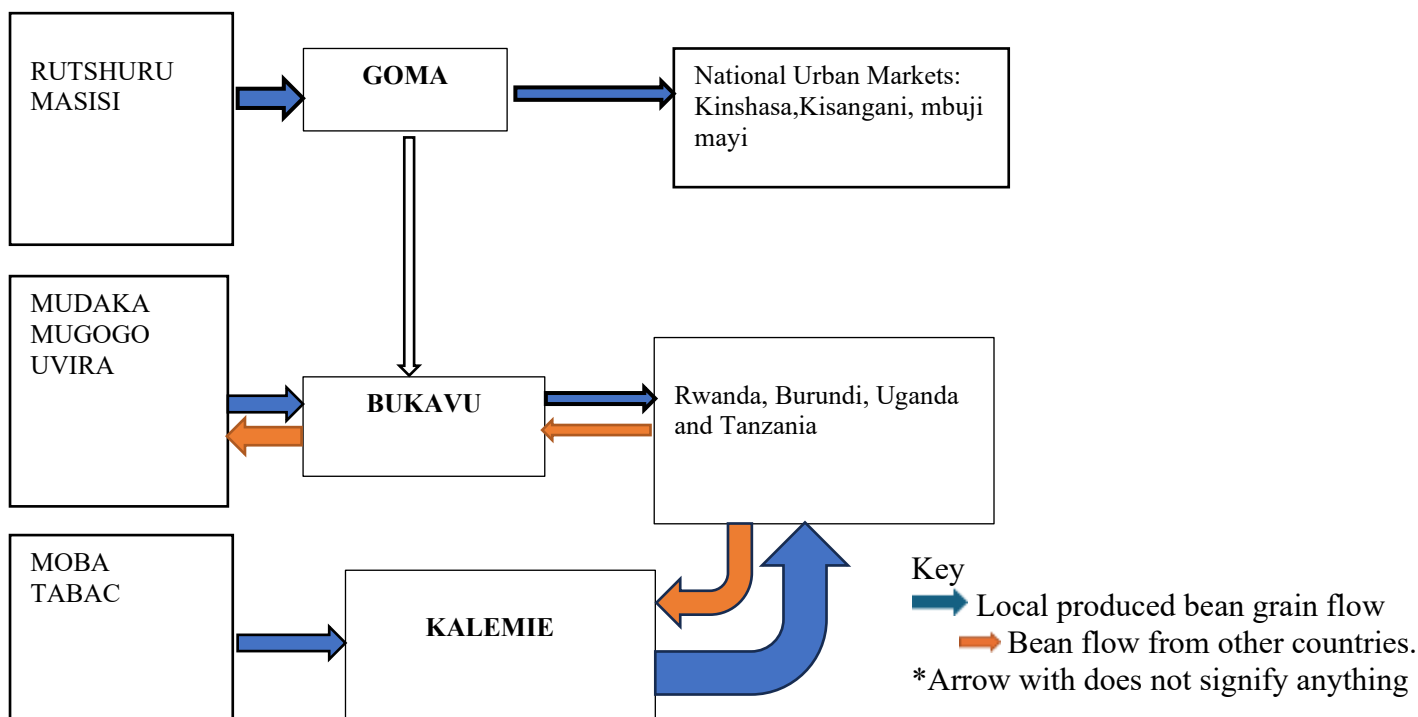


Figure 4: Main bean trade routes in eastern DRC and surrounding countries.

Further analysis shows the spatial disparities in average bean prices as displayed in Table 1. In 2024, the highest retail prices were recorded in Bukavu (USD 1.23/kg) and Mugogo (USD 1.38/kg), both likely affected by local production deficits and high transport or transaction costs. In contrast, traditional production zones such as Moba (USD 0.52/kg) and Rutshuru (USD 0.80/kg) showed lower prices, consistent with stronger local supply and lower dependence on imported beans. Intermediate prices in Masisi (USD 0.85/kg) and Uvira (USD 0.84/kg) further suggest their dual role as production and transit points.

Table 1: Average Annual Retail Price of Beans by Market across provinces (USD/kg)

Year	Bukavu	Goma	Masisi	Rutshuru	Mudaka	Mugogo	Uvira	Kalemie	Moba	Tobacco
2017	0.42	0.3	0.25	0.23	0.48	0.48	0.24	0.3	0.22	0.32
2018	0.46	0.38	0.28	0.24	0.5	0.5	0.27	0.31	0.23	0.34
2019	0.48	0.4	0.32	0.3	0.52	0.52	0.29	0.34	0.23	0.4
2020	0.52	0.42	0.37	0.34	0.53	0.54	0.34	0.44	0.25	0.55
2021	0.57	0.51	0.38	0.37	0.55	0.61	0.45	0.46	0.28	0.57
2022	0.71	0.62	0.52	0.42	0.58	0.71	0.58	0.42	0.3	0.68
2023	1.04	0.87	0.73	0.65	0.81	1.07	0.77	0.55	0.34	0.71
2024	1.23	0.97	0.85	0.8	1.2	1.38	0.84	1	0.52	0.9

To assess spatial market integration, Table 2 presents average monthly price differentials and their corresponding coefficients of variation (CV) for selected market pairs. The CV reflects the stability of price margins between two markets; higher values suggest weaker integration and/or volatile linkages. Among the observed pairs, Moba–Kalemie and Uvira–Bukavu exhibit the highest CVs (1.558 and 1.360, respectively), suggesting limited market integration. These figures are consistent with their logistical and geographic challenges: long travel distances (over 500 km for Moba–Kalemie by lake) and poor road connectivity. Conversely, market pairs with shorter distances, such as Mudaka–Bukavu and Mugogo–Bukavu, show relatively low CVs, reflecting tighter price linkages and better market integration.

Table 2: Average Monthly Price Differentials and Coefficient of Variation.

Walk Channel	Binding mode	Distance (Km)	Mean price difference	Coefficient of variation
Rutshuru–Goma	Road	68.4	0.11	0.300
Masisi -Goma	Road	78.4	0.06	0.420
Bukavu - Goma	Lake	208	0.32	0.492
Mudaka – Bukavu	Road	15	0.03	0.340
Mugogo – Bukavu	Road	25	1.5	0.252
Uvira-Bukavu	Road	120	0.39	1,360
Moba -Kalemie	Lake	508	0.48	1,558
Tobacco-Kalemie	Road	10	0.1	0.434

5.2. Bivariate Correlation Analysis

To further explore price co-movement, a bivariate correlation analysis using logarithmic monthly prices was conducted. A resultant correlation matrix based on monthly logarithmic retail prices generated and presented in Figure 5. The results indicate generally high and positive correlations ($r > 0.80$) among most market pairs, implying a certain degree of co-movement and interdependence in bean prices across locations.

However, weaker correlations are observed in pairs involving Moba (e.g., Moba–Bukavu: $r = 0.59$; Moba–Goma: $r = 0.70$) and Uvira–Bukavu ($r = 0.75$). These lower coefficients could be attributed to poor market connectivity, differences in supply sources, and logistical barriers. It is important to note that while correlation suggests price co-movement, it does not confirm market integration due to the potential influence of common shocks or seasonality. Therefore, more robust econometric techniques, such as cointegration analysis, are necessary to confirm long-run market linkages.

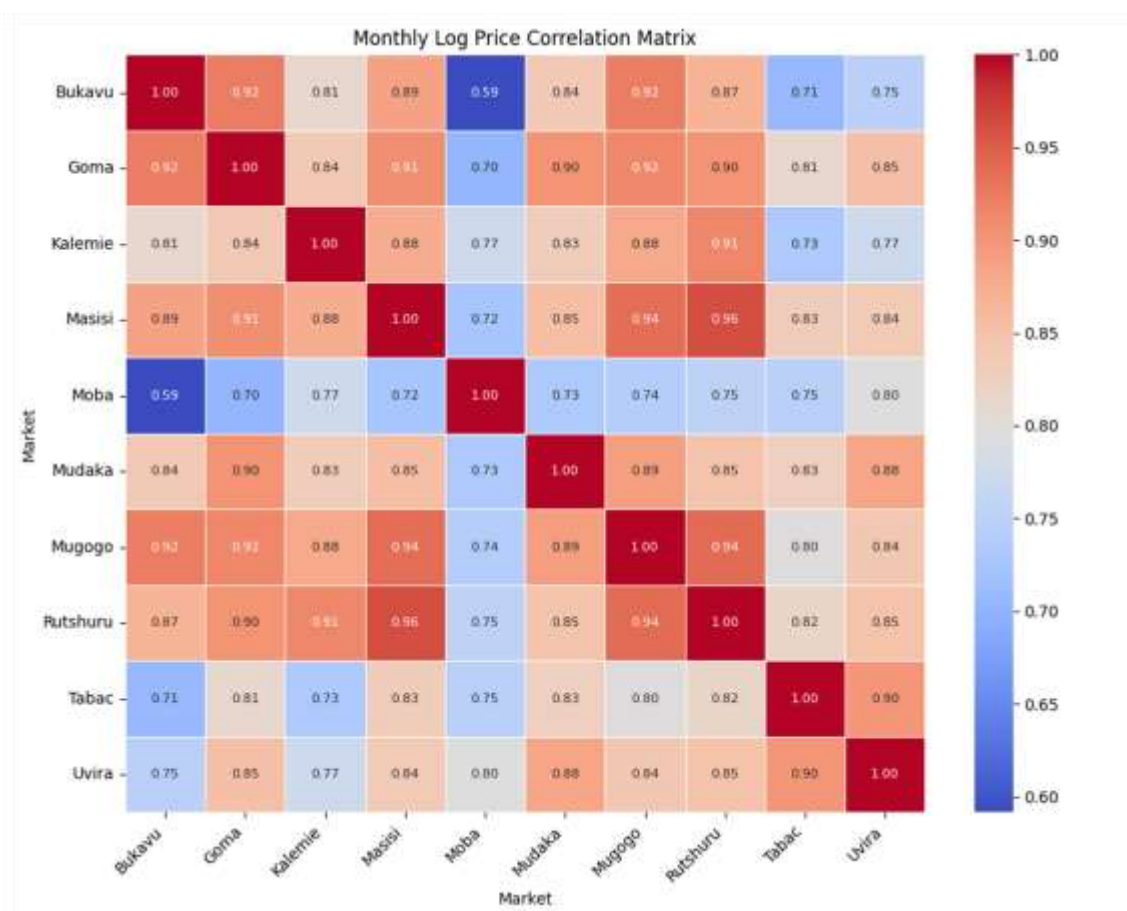


Figure 5: Correlation matrix of monthly logarithmic prices

5.3. Econometric Results

5.3.1. Stationarity Test

The first step in conducting any reliable time-series econometric analysis is to examine the stationarity of the data. In this study, the Augmented Dickey-Fuller (ADF) test was employed to determine whether the monthly bean price series from various markets exhibit unit roots, implying non-stationarity. The results are presented in Table 3.

At all levels, the ADF test statistics for all the market price series (Goma, Rutshuru, Masisi, Bukavu, Mudaka, Uvira, Mugogo, Kalemie, Tobacco, and Moba) were found to be greater than the critical values at the 1%, 5%, and 10% levels of significance, which means the null hypothesis of a unit root could not be rejected. In practical terms, this implies that the bean price series are non-stationary in their original form, something that could compromise regression analysis by leading to spurious results.

However, upon first differencing the data, the ADF test statistics fell below the respective critical thresholds, thus rejecting the null hypothesis for all price series. For reference, the critical values for the ADF test with a drift (null: unit root) at levels are -2.71 (1%), -2.61 (5%), and -2.43 (10%). For the differenced data, where the null remains a unit root and the alternative implies stationarity around the mean, the critical values are slightly relaxed to -2.59 (1%), -2.04 (5%), and -1.72 (10%). Comparing these thresholds with the ADF values obtained after differencing (e.g., Goma: -3.836, Rutshuru: -4.565, Moba: -4.566), it is evident that all test statistics exceed the critical values in absolute terms. These thresholds confirm the transformation of the price series into stationary variables suitable for cointegration analysis. Consequently, it can be concluded that each series is integrated of order one, denoted as $I(1)$. This outcome satisfies one of the key prerequisites for cointegration analysis, where non-stationary series at levels must become stationary after first differencing to validate further tests of long-run relationships.

Table 3: ADF Test Results on Monthly Bean Price Series

SERIES	ADF TEST	1st Order of DIFFERENCE
Goma	- 1.30	- 3,836
Rutshuru	- 1.56	-4.565
Masisi	- 1.23	- 3.73
Bukavu	- 1.04	- 4.122
Mudaka	- 1.89	- 5,482
Uvira	- 1.46	- 7,132
Mugogo	- 1.86	- 3,873
Kalemie	- 1.20	- 4,897
Tobacco	- 1.23	- 3,264
Moba	- 1.27	- 4,566

5.3.2. Cointegration Test and ECM Estimation

Following the confirmation of non-stationarity at level and stationarity at first difference, the next step was to assess whether a long-run equilibrium relationship exists among the selected markets. This was achieved by estimating Error Correction Models (ECMs) for seven market pairs, where peripheral markets were regressed against three central hubs that included Goma, Bukavu, and Kalemie.

The results, presented in Table 4, reveal important insights into the integration of bean markets across the study region. The negative and statistically significant coefficients of the lagged error correction terms (R_{jt-1}) in most market pairs indicate that deviations from the long-run equilibrium are partially corrected over time. The magnitudes of these coefficients reflect the extent of this correction, while their significance confirms the existence of a cointegrating relationship. Notably, the Rutshuru-Goma and Masisi-Goma market pairs exhibit strong cointegration, with adjustment coefficients of -0.044 and -0.020 respectively. Similarly, Bukavu's satellite markets (Mudaka, Mugogo, and Uvira) also exhibit error correction behavior, although the speed and magnitude of adjustment vary. This variation shows that, while the cointegration may exist, the error correction mechanism may be weak or even absent. This observation aligns with the earlier descriptive and correlation analysis, which indicated weaker price transmission between these distant or less accessible markets.

Table 4: Error Correction Model (ECM) Estimates for Market Integration

Market channel	Intercept	$P_{it} - P_{it-1}$	$R_{jt} - R_{jt-1}$	R_{jt-1}	Adj R^2	DW
Rutsuru – Goma	-0.04 (-2.028)	-0.327(3.514)	0.475(2.030)	-0.044* (-0.675)	0.8563	1.816***
Masisi – Goma	-0.038(-2.229)	-0.325(-2.979)	0. 414(2.123)	-0.020 ** (0.126)	0.9124	1.701***

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Mudaka – Bukavu	-0.030(1.741)	-0.047(-3.654)	0.317(2.675)	0.213 (2.164)	0.7883	1.631***
Uvira-Bukavu	-0.210(-3.765)	-0.093 (-4.12)	0.304(1.955)	0.095*** (0.842)	0.7237	1.452***
Mugogo – Bukavu	-0.271(-1.548)	-0.271(2.608)	0.514(3.032)	-0.116 (-1.535)	0.8761	1.603***
Tobacco–Kalemie	-0.307(1.567)	-0.370(-2.09)	0.370(0.697)	0.113 (0.077)	07.037	1.872***
Moba -Kalemie	-0.202(3.134)	-0.529 (-5.24)	0.359(1.876)	-0.050** (-0.781)	0.6361	1.967***

***, **, * statistical significance at 1%,5% and 10%, respectively

5.3.3 Short-Term Price Dynamics and the Bean Market Integration Index (BMI)

Short-term market integration is examined using the Bean Market Integration (BMI) Index, which quantifies the responsiveness of peripheral market prices to shocks or changes in central reference markets. Table 5 presents the regression results used to compute BMI values for each market pair.

A BMI value close to 1 indicates a strong and efficient short-run transmission of price signals, implying that local markets are quick to respond to changes in the central market. The results shows that the Rutshuru-Goma and Masisi-Goma pairs have BMI values of 0.85 and 0.82, respectively, confirming strong short-term integration with the Goma market. That is, if the price in Goma changes by 1% during period $t - 1$, this leads to an increase of 0.85% in the price in the Rutshuru market. Similar trends are observed in Bukavu's satellite markets, such as Mudaka (BMI = 0.81) and Mugogo (BMI = 0.79).

In contrast, BMI values for Uvira-Bukavu (2.44) and Moba-Kalemie (5.27) are unusually high. Such values suggest a divergence from the standard market integration pattern. In practical terms, these inflated BMI figures could be indicative of weak price transmission mechanisms or the absence of any meaningful cointegration. Instead of converging towards central market prices, these local prices appear disconnected, perhaps due to poor infrastructure, information asymmetries, or regional trade barriers.

Table 5: BMI regression analysis for bean markets

Regions (Reference)	$\beta_0(t\text{-stat})$	$\beta_1(t\text{-stat})$	$\beta_2(t\text{-stat})$	$\beta_3(t\text{-stat})$	BMI
Rutshuru (Goma)	- 0.125(-0.767)	0.237 (2.383) *	0.433 (7.657) ***	0.745 (5.643) ***	0.85
Masisi (Goma)	0.786 (0.632)	0.278 (2.645) **	0.976 (8.997)***	0.683(0.879)	0.82
Mudaka (Bukavu)	0.865 (1.673) *	0.122 (1.246)	0.871 (10.767) ***	0.746 (2.657) **	0.81
Mugogo (Bukavu)	0.534 (1.121)	0.243 (1.567) *	0.621 (10.586) ***	0.599 (2.567) **	0.79
Uvira (Bukavu)	0.767 (1.216)	3,887 (0.676)	0.597 (14.974) ***	0.578 (7.984) ***	2.44
Moba (Kalemie)	0.297 (2.335) **	0.686 (1.458)	0.745 (17.213) ***	0.851 (0.699)	5.27
Tobacco (Kalemie)	0.897 (1.798) *	0.243 (1.569) *	0.877 (11.345) ***	0.978 (2.335) ***	0.86

***, **, * statistical significance at 1%,5% and 10%, respectively

5.3.4. Long-Term Adjustment Speed (Coefficient d_1)

To complement the short-term analysis, Table 6 summarizes the long-term adjustment speeds represented by the absolute values of the error correction term coefficients ($|d_1|$), alongside the previously calculated BMI values. These coefficients provide a direct measure of how quickly deviations from the long-term equilibrium are corrected across different market pairs.

The findings reveal varying speeds of adjustment across the regions. Rutshuru-Goma ($|d_1| = 0.37$) and Mudaka-Bukavu ($|d_1| = 0.36$) exhibit the fastest adjustment, with approximately 37% and 36% of the price deviations being corrected in the subsequent month, respectively. This suggests a highly efficient long-term relationship between these market pairs. Other markets such as Masisi-Goma ($|d_1| = 0.32$), Mugogo-Bukavu (0.34), and Tobacco-Kalemie (0.33) show moderately fast adjustments, indicating a robust but slightly delayed response to price changes. On the other hand, Moba-Kalemie ($|d_1| = 0.26$) and Uvira-Bukavu (0.27) represent the slowest speeds of adjustment. The slower response may be attributed to geographical remoteness, transportation

bottlenecks, or weaker market infrastructure that inhibits effective price signal transmission. The average speed of adjustment across all market pairs stands at around 32%, reinforcing the idea that while integration exists, its strength varies substantially across locations.

Table 6: Market integration indicators: Speed of adjustment ($|d_1|$) and BMI

Walk	Indicators market integration		
Local	Reference	Long -term adjustment speed d_1	Short- term integration MCI0
Rutsuru	Goma	0.37	0.86
Masisi	Goma	0.32	0.87
Mudaka	Bukavu	0.36	0.84
Mugogo	Bukavu	0.34	0.82
Uvira	Bukavu	0.27	2.34
Moba	Kalemie	0.26	4.28
Tobacco	Kalemie	0.33	0.85

These findings suggest that market integration in the region is generally present but heterogeneous. Proximity to central markets, infrastructure quality, and trading volume appear to influence the degree and speed of both short- and long-term price adjustments. Peripheral markets with strong links to central hubs respond more swiftly and accurately to price signals, enhancing market efficiency and potentially stabilizing consumer and producer prices. Conversely, more isolated markets require targeted policy interventions to improve connectivity and ensure better integration within the regional food system.

6. CONCLUSION AND RECOMMENDATIONS

This study examined the spatial integration of bean market prices in South Kivu, North Kivu, and Tanganyika provinces in the DRC using monthly price data from 2017 to 2024. By employing cointegration techniques, including Error Correction Models (ECM) and the Market Connection Index (MCI), the study assessed the long-term and short-term price relationships between key market pairs.

The findings reveal that all the bean price series were non-stationary in levels but stationary in first differences, indicating long-term integration across the markets. Evidence of cointegration between most market pairs suggests that these markets are not entirely segmented, allowing for some level of spatial arbitrage. However, the speed of adjustment toward long-run equilibrium varies. On average, 32% of price disequilibria are corrected monthly, with faster adjustments observed in geographically closer markets like Rutshuru-Goma, while slower adjustments were noted in more distant areas such as Moba-Kalemie and Uvira-Bukavu.

Short-term price transmission also differed across market pairs, with stronger price links in well-connected markets and weaker connections in isolated regions. This variation in integration, driven by geographic and infrastructural factors, suggests that while markets are interconnected, the flow of price signals is hindered in some areas, particularly where transportation and communication are limited. Additionally, the significant rise in bean prices over the study period underscores the vulnerability of markets in the region, where many people live below the poverty line.

Therefore, to address this challenges of market imperfection and heterogeneity in Eastern Congo for the benefit of producers and consumers who are vulnerable to local price shocks, several interventions are recommended. First, investment in transport infrastructure to reduce transaction costs and accelerating price adjustments, particularly for remote markets like Moba and Uvira is necessary. Improved roads and transport routes would enable more efficient market integration, benefiting both producers and consumers. Strengthening Market Information Systems (MIS) is also essential to reduce information asymmetry. Access to timely and accurate price data would empower producers and traders to make informed decisions, improving market efficiency and price transmission. Further, efforts to stabilize the region and improve security are also crucial. Insecurity remains a barrier to smooth trade flows, hindering effective market integration. Policies aimed at enhancing stability will help foster a more conducive environment for market activity. Finally, supporting local actors through capacity-building initiatives, such as organizing producers into cooperatives, can enhance their bargaining power and market access. This would help improve their resilience to price shocks and strengthen their position within the market.

Limitations of the study

This study has a few limitations that should be considered. First, by using monthly data, it may miss important market changes that happen within shorter time periods. Additionally, the analysis focuses on price data only and does not consider traded volumes or transaction costs, which are also crucial for understanding market dynamics. The use of linear models, such as the Error Correction Model (ECM), may not fully capture complex or uneven price transmission patterns. Lastly, specific shocks, such as those caused by conflict or climate-related events, were not directly included in the analysis.

Future research

Future research could build on this study by using higher-frequency data, such as weekly prices, to capture more detailed market dynamics. It would also be valuable to incorporate transport costs and indicators of insecurity, as these factors significantly affect market integration. Applying nonlinear models, such as Threshold Autoregressive (TAR) models, could provide deeper insights into the complexity of price transmission. Additionally, a comprehensive value chain analysis, including trade margins at each stage, would offer a more complete understanding of market behavior and integration.

Conflict of Interest

The authors declare no conflict of interest related to the publication of this paper.

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REFERENCES

1. Amankwah-Amoah, J., Boso, N., & Debrah, Y. A. (2018). Africa rising in an emerging world: an international marketing perspective. *International Marketing Review*, 35(4), 550-559. <https://doi.org/10.1108/imr-02-2017-0030>
2. Amikuzuno, J. and Ogundari, K. (2015). A meta-regression analysis of price transmission estimates in sub-saharan africa. *Outlook on Agriculture*, 44(4), 309-314. <https://doi.org/10.5367/oa.2015.0221>
3. Baidya, M. K. and Maity, B. (2023). The interplay between sales and marketing expenditures: an econometric approach in the b2b market. *Journal of Business & Industrial Marketing*, 39(5), 967-978. <https://doi.org/10.1108/jbim-01-2023-0047>
4. Barrett, C.B. (1996). Market analysis methods: Are our enriched toolkits well-suited to enlivened markets? *American Journal of Agricultural Economics*, 78 (3), 825–829. <https://doi.org/10.2307/1243313>
5. Boaz, S. W., Eliezah, K., David, K., & Franklin, M. (2022). Response of common beans (*phaseolus vulgaris* l.) to seed treatment in central kenya. *African Journal of Agricultural Research*, 18(2), 95-105. <https://doi.org/10.5897/ajar2021.15808>
6. Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55 (2), 251–276. <https://doi.org/10.2307/1913236>
7. FAO. (2022). Food and Agriculture Organization of the United Nations.
8. Food and Agriculture Organization of the United Nations (FAO). (2025). *FAOSTAT: Producer Prices – Annual*. <https://www.fao.org/faostat/en/#data/PP>
9. Guesmi Khaled, Nguyen Duc Khuong. Financial integration of emerging stock markets: a regional analysis. In: *Applied Economics*, volume 64 no. 2, June 2011. pp. 143-180 ; doi : <https://doi.org/10.3406/ecoap.2011.3570>
10. Ihle, R., J. Amikuzuno and S.V. Cramon- Taubadel , 2010. Market Integration with and Without Direct Trade: The Case of Tomatoes in Ghana. *Journal of Development Economics*, vol. 18, pp. 21-46. <https://doi.org/10.22004/ag.econ.51402>
11. Kmenta, J. (2015). Time series econometrics: a critique. *Open Journal of Applied Sciences*, 05(12), 841-843. <https://doi.org/10.4236/ojapps.2015.512081>
12. Ling, S., McAleer, M., & Tong, H. (2015). Frontiers in time series and financial econometrics: an overview. *Journal of Econometrics*, 189(2), 245-250. <https://doi.org/10.1016/j.jeconom.2015.03.019>
13. Lisciani, S., Marconi, S., Le Donne, C., Camilli, E., Aguzzi, A., Gabrielli, P., ... & Ferrari, M. (2024). Legumes and common beans in sustainable diets: nutritional quality, environmental benefits, spread and use in food preparations. *Frontiers in Nutrition*, 11, 1385232. <https://doi.org/10.3389/fnut.2024.1385232>
14. Mumbeya, P. N. (2011). *A value chain and market integration analysis of the cassava market in the Democratic Republic of Congo*. University of Pretoria (South Africa). <http://hdl.handle.net/2263/26621>
15. National Agricultural Statistics Service (NAAS): summary tables of agricultural statistics. 2024.
16. Nchanji, E. B., Lutomia, C. K., Chirwa, R., Templer, N., Rubyogo, J. C., & Onyango, P. (2021). Immediate impacts of covid-19 pandemic on bean value chain in selected countries in sub saharan africa. *Agricultural Systems*, 188, 103034. <https://doi.org/10.1016/j.agry.2020.103034>
17. Templer, N., Birachi, E. A., & Rubyogo, J. C. (2022). Seed and market systems of the Eastern DRC: A fragile state case study. <https://hdl.handle.net/10568/130766>
18. Timmer, C. P. (Ed.). (2019). *The corn economy of Indonesia*. Cornell University Press.
19. Traore, F., & Diop, I. (2021). Measuring integration of agricultural markets. AGRODEP Technical TN-18. Washington, DC: International Food Policy Research Institute (IFPRI). <https://doi.org/10.2499/p15738coll2.134308>