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Review Article

The Application of the Markov-Switching Model to Examine the Relationship between Commodity Prices and ASEAN+3 Countries' Financial Instability

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ABSTRACT

This study investigates the nonlinear and regime-dependent relationship and causal link between financial stress in ASEAN+3 economies and global commodity price fluctuations over the period 1995:1–2023:8, using the Markov-Switching Vector Error Correction Model MSIA(2)-VECM(7). The model allows the identification of distinct behaviors during economic expansions and recessions, with Regime 1 representing the boom phase and Regime 2 the recession phase. Empirical findings reveal that during expansionary periods, there is a significant one-way causal relationship in which changes in commodity prices lead to financial stress, indicating limited external price influence. In contrast, during recessions, a significant two-way causal relationship is observed: increases in global commodity prices exacerbate financial stress, while financial stress shocks—through effects on production costs, investment, global demand, and exchange rates—in turn affect commodity prices. Lagged financial stress exhibits self-reinforcing and self-correcting mechanisms, reflecting the effectiveness of targeted policy interventions such as liquidity injections, monetary easing, and fiscal support in restoring stability. Analysis of regime transition probabilities demonstrates that the boom regime is more stable and persistent than the recession regime, emphasizing the importance of regime-specific policy measures. Based on these results, policymakers should prioritize stabilizing interventions during downturns, continuously monitor commodity price trends, and enhance economic resilience through trade diversification and improved trade balances to mitigate the asymmetric impact of global commodity price shocks. Overall, the study highlights the critical role of regime-dependent and causal-informed policy actions in maintaining financial stability and supporting sustainable economic growth in ASEAN+3 economies. It provides quantitative insights to help policymakers and financial institutions strengthen resilience to external market volatility.

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1. Introduction

Fluctuations in global commodity prices have increasingly emerged as a critical concern for financial stability, particularly in emerging and developing economies. Commodity markets, encompassing metals, energy, and agricultural products, are influenced by a complex interplay of factors, including macroeconomic conditions, geopolitical events, supply-demand shocks, and international economic policies (Boateng et al., 2022; Kilian and Murphy, 2014). Historical episodes, such as the 2008 global financial crisis, the COVID-19 pandemic, and regional conflicts, have highlighted the potential for sudden and significant price swings that can affect trade balances, inflationary pressures, and overall economic resilience (Kyei et al., 2023). The ongoing financialization of commodities has significantly changed market dynamics. As these assets are increasingly linked to financial instruments and institutional investment, price movements have become increasingly sensitive to global financial conditions and investor sentiment (Basak and Pavlova, 2016; Goldstein and Yang, 2022).

Previous studies have examined the correlation between financial instability and commodity price volatility; however, much of the existing literature primarily focuses on linear relationships or single-market effects (Tang and Zhu, 2016; Natoli, 2021). Nevertheless, real-world dynamics are often nonlinear and regime-dependent, particularly during periods of economic stress and recovery. For instance, commodity price shocks may amplify financial stress during downturns, whereas their effects may be dampened in periods of economic expansion due to stronger liquidity conditions and active policy interventions (Hamilton, 1989; Shahbaz et al., 2019). Traditional linear models, therefore, risk underestimating the asymmetric impact of commodity fluctuations on financial stability.

The present study investigates the dynamic and nonlinear interaction between financial stress and global commodity prices in ASEAN+3 economies using a Markov Switching Vector Error Correction Model (MS-

VECM). This approach enables the identification of regime-dependent dynamics, capturing distinct behaviors during periods of economic expansion and contraction. Unlike structural models that impose exogenous regime shifts, the MS-VECM endogenously determines regime changes based on probability estimates, providing a flexible and robust framework for analyzing financial-commodity interactions over time.

This research addresses a significant gap in the literature. Although prior studies have separately analyzed the effects of financial stress or commodity volatility, few have explored their time-varying, nonlinear interactions and causal relationships within a multivariate framework with regime-switching properties. By applying the MS-VECM to monthly data spanning 1995:1 to 2023:8, this study captures the effects of major global crises, including the 1997–1998 Asian Financial Crisis (AFC), the 2008 Global Financial Crisis (GFC), the SARS outbreak, and the COVID-19 pandemic, on ASEAN+3 financial systems. The analysis highlights how these economies respond differently to external shocks depending on the prevailing economic regime, shedding light on periods of vulnerability and resilience.

Empirical findings indicate that the interaction between financial stress, measured by the first difference of the Financial Stress Index (DFSI), and global commodity prices is nonlinear, asymmetric, and causally interconnected. During periods of economic expansion, the effects of commodity price changes on financial stress are generally weak and statistically insignificant. Conversely, during recessionary periods, rising commodity prices significantly exacerbate financial stress, reflecting higher import costs, inflationary pressures, and trade imbalances. Lags of DFSI and commodity prices also exhibit Granger-causal effects on themselves and on each other in the recession regime, indicating strong persistence and mutual feedback in times of financial vulnerability. Furthermore, regime transition probabilities suggest that boom periods tend to be more persistent and stable than recessions, emphasizing the importance of regime-specific considerations in macroeconomic planning and policy interventions.

This study contributes to the literature in four main ways: (i) applying the MS-VECM framework to capture nonlinear, regime-dependent, and causally linked interactions between financial stress and commodity prices, (ii) employing DFSI to account for key crises and financial stress dynamics over nearly three decades, (iii) providing a long-term empirical assessment in the ASEAN+3 context, and (iv) offering policy-relevant insights for targeted interventions and resilience strategies during periods of heightened financial vulnerability. The remainder of the paper is structured as follows: Section 2 presents the theoretical background; Section 3 reviews the related literature; Section 4 details the data, methodology, and empirical results; and Section 5 concludes with key findings and policy implications.

2. Literature review

Previous studies indicate that financial stress can significantly influence commodity price fluctuations through multiple channels. One of the primary drivers of commodity price volatility is economic uncertainty, as commodity prices are shaped by aggregate supply and demand dynamics (Bakas and Triantafyllou, 2018). Financial stress also leads investors to rebalance their portfolios, which, in turn, affects commodity prices. This effect is partly linked to the financialization of commodities, which has increased their importance in investment portfolios (Behmiri et al., 2021; Adams and Glück, 2015). Financial stress indices, such as the Kansas City Financial Stress Index (KCFSI), capture the lagged effects of uncertainty in financial markets through multiple indicators, including yield spreads, asset prices, and implied market conditions (Hakkio and Keeton, 2009; Chen et al., 2023).

On the other hand, commodity price volatility can itself exacerbate uncertainty in the financial system. Sharp declines in commodity prices can reduce revenues for exporting countries, potentially increasing loan defaults, decreasing credit demand, and weakening banks' capital adequacy (Abaidoo et al., 2021). Fluctuations in commodity prices also affect the profitability of firms operating in commodity-related sectors, which, in turn, can influence economic growth, export revenues, borrowing and lending activities, and overall financial stability (Kinda et al., 2018; Enwereuzoh et al., 2021). Reduced export revenues can lead to currency devaluation, increased bank withdrawals, and liquidity pressures, undermining consumer confidence and threatening public purchasing power. Moreover, lower export income can constrain government budgets, reducing their ability to service debts or fund social programs, thereby further impacting the banking system and financial stability (Abaidoo et al., 2021; Kinda et al., 2018).

Despite these well-documented links, existing literature often examines financial stress or commodity price volatility in isolation. Studies by Davig et al. (2010) and Hubrich and Tetlow (2015) analyzed financial stress indices but did not incorporate commodity price fluctuations. Nazlioglu and Soytas (2012) used the Cleveland Financial Stress Index to demonstrate risk transmission from financial markets to energy markets, while Reboredo and Uddin (2016) identified negative Granger causality in certain quantiles of commodity returns. Other studies, including Wan and Kao (2015), Ahmadi et al. (2016), and Behmiri et al. (2021), examined energy price responses to financial conditions using threshold vector autoregressive (TVAR) models, and Shahbaz et al. (2019) reported varying degrees of association between commodity prices and financial instability. Chen et al. (2023) employed MS-VAR models to show that escalating financial stress amplifies both the volatility of commodity indices and the volatility of individual commodity prices. Similarly, Kyei et al. (2023) documented the influence of cocoa, gold, and crude oil prices on Ghana's banking sector Financial Stress Index (BsFSI), supporting adaptive market hypothesis perspectives.

However, few studies have systematically examined the dynamic, nonlinear, and causal interaction between financial stress and commodity prices in ASEAN+3 economies. Most prior research relies on linear or fixed-state models. It largely ignores the regional context, despite ASEAN+3 representing a critical economic cluster with distinctive financial and commodity market structures, high trade interdependence, and varying exposure to global shocks. Consequently, there remains a significant gap in understanding how financial stress interacts with commodity price fluctuations over time under different economic conditions, particularly in emerging and developing markets in Southeast and East Asia. Moreover, previous studies rarely investigate the direction of causality, especially whether financial stress drives commodity price movements, whether commodity price shocks amplify financial stress, or whether a feedback mechanism exists.

To address these limitations, the present study employs a Markov Switching Vector Error Correction Model (MS-VECM). This approach allows for the capture of regime-dependent dynamics, the distinction between behaviors during periods of economic expansion (booms) and contraction (recessions), and the accurate reflection of nonlinear interactions. Unlike linear models, the MS-VECM accommodates structural changes in the economy and financial system—such as global crises, policy interventions, and external shocks—providing a flexible and realistic framework for analyzing both the magnitude and direction of causal effects between financial stress and commodity price volatility. By applying MS-VECM to monthly data from 1995:1 to 2023:8 for ASEAN+3 countries, this study fills a critical gap in the literature, offering a region-specific, time-varying, and causality-informed analysis of interactions between financial stress and commodity markets.

In summary, the literature suggests that financial stress significantly drives commodity price shocks. However, prior studies largely overlook nonlinear dynamics, regime dependence, causal directionality, and the ASEAN+3 context. By employing the MS-VECM framework, this study provides a comprehensive, evidence-based assessment of how financial stress and commodity price volatility interact over time, highlighting periods of vulnerability and resilience. The findings provide practical insights for policymakers and financial institutions seeking to enhance financial stability, mitigate feedback effects, and strengthen economic resilience across ASEAN+3 economies.

3. Methodology

This section empirically examines the relationship between financial instability and the global commodity price index across ASEAN+3 countries[1] using the Markov-Switching Vector Error Correction Model (MS-VECM). Unlike the MS-VAR, the MS-VECM incorporates error-correction terms to account for cointegration among the variables, thereby addressing the potential for spurious regression and capturing both short- and long-term dynamics. The MS-VECM also enables regime-dependent behavior, in which the data are automatically segmented into distinct regimes according to the Markov switching process. This allows for the examination of how relationships evolve across different states.

This study analyzes difference series, namely DFSI (financial stress index difference) and DLCOMM (first difference of the logarithm of the commodity price index). The focus is on short-term dynamics while maintaining the long-term equilibrium relationship implied by cointegration. Following the framework outlined by Chen et al. (2023), the model can be expressed as follows:

$$X = (DFSI, DLCOMM) \tag{1}$$

DFSI: first difference of the Financial Stress Index (FSI) is a metric evaluated in accordance with the research of Park et al. (2014). It comprises five primary components.[2] The FSI data include several major crises that occurred during the sample period (1995:1–2023:8), such as the Asian Financial Crisis (AFC), the Global Financial Crisis (GFC), the SARS outbreak, and the COVID-19 pandemic. The abbreviations used in the dataset are as follows: AFC = Asian Financial Crisis, ASEAN = Association of Southeast Asian Nations, COVID-19 = coronavirus disease, GFC = global financial crisis, PRC = People's Republic of China, SARS = Severe Acute Respiratory Syndrome, US = United States.

1. It includes Hong Kong (China), Japan, the Republic of Korea, and Southeast Asia. ASEAN and Southeast Asia include Indonesia, Malaysia, the Philippines, Singapore, and Thailand.
2. Data source: https://aric.adb.org/database/fsi

The regional classification follows standard ADB conventions: ASEAN+3 encompasses Hong Kong (China), Japan, the People's Republic of China, the Republic of Korea, Taipei (China), and the five founding ASEAN members (Indonesia, Malaysia, the Philippines, Singapore, and Thailand). Advanced Asian economies include Australia and Japan, while developing Asia covers East Asia (excluding Japan), South Asia, and Southeast Asia.

$$FSI = \beta + Stockreturns + Stockvolatility + Debtspreads + EMPI \qquad (2)$$

The Financial Stress Index (FSI) is constructed following Park et al. (2014) and comprises five distinct components. The first component captures banking sector risk through the beta coefficient, computed as the ratio of the covariance between banking stock returns and market returns to the market variance: $\beta = \frac{cov(r_m, r_b)}{var r_m}$. The second component measures equity market returns as the log-difference of the stock price index: $\gamma_t = \mathrm{Ln}(P_t) - \ln(P_{t-1})$. where declines indicate rising stress. The third component accounts for equity market volatility, estimated via a GARCH(1,1) process: $\sigma_t^2 = \omega + \varphi_1 \varepsilon_{t-1}^2 + \varphi_2 \sigma_{t-1}^2$

where σ_t^2 denotes the variance, and ε represents the regression error:

$$\gamma_t = a_{i,t} + \beta \gamma_{t-1} + \varepsilon_{i,t}$$

The fourth component reflects sovereign debt stress through yield spreads between 10-year and 2-year government bonds. Finally, the exchange market pressure index (EMPI) combines currency depreciation and reserve losses: $EMPI_{i,t} = \frac{(\Delta e_{i,t} - \mu_{i,\Delta e})}{\sigma_{i,\Delta e}} - \frac{(\Delta RES_{i,t} - \mu_{i,\Delta RES})}{\sigma_{i,\Delta RES}}$, where higher values signal greater forex market pressure.

Figure 1 illustrates the level of financial instability in ASEAN+3 countries from 1995:1 to 2023:8 using monthly data.

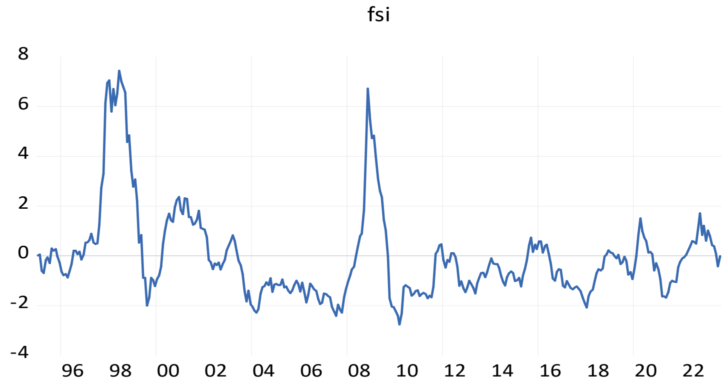

Fig 1. The financial instability of ASEAN+3 countries from 1995:1 to 2023:8

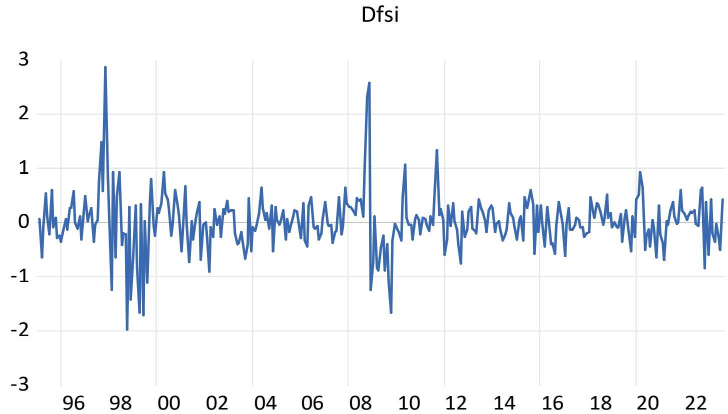

Fig 2. The value of the difference in the financial instability of ASEAN+3 countries from 1995:1 to 2023:8

DLCOMM is the first difference of the logarithm of the commodity price index measured by indices denominated in nominal US dollars since the base year of 2010. The global commodity price index comprises energy and non-energy sectors, which account for 67% and 33% of the index, respectively. The energy sector includes coal (4.7%), crude oil (84.6%), and natural gas (10.8%). The non-energy sector consists of metals (31.6%), agriculture (64.9%), and fertilizer (3.6%). Within the agricultural sector, beverages account for 8.4%, food for 40%, and raw materials for 16.5%. The food sector is further divided into grains (11.3%), oils and meals (16.3%), and other dietary items (12.4%). Finally, the precious metals sector comprises gold (77.8%), silver (18.9%), and platinum (3.3%).

Figures 3 and 4 illustrate the logarithm of the global commodity price and its discrepancy from 1995:1 to 2023:8 as measured by the aforementioned indicators.

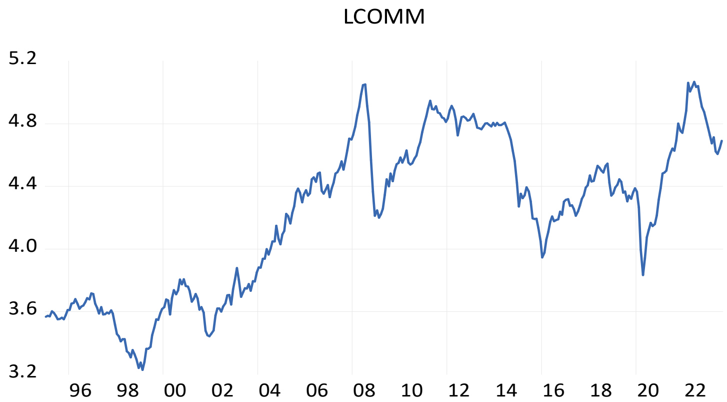

Fig 3. The logarithmic value of the global commodity price index from 1995:1 to 2023:8

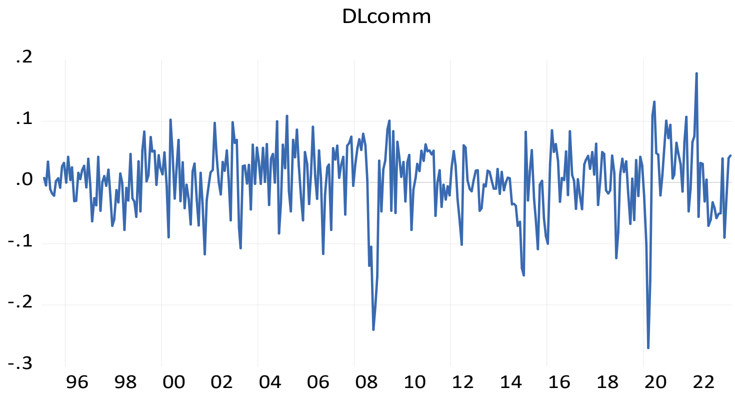

Fig 4. The value of the differenced logarithm of the commodity price index from 1995:1 to 2023:8

3.1. Markov-Switching Vector Error Correction Model

This section empirically examines the relationship between financial instability and the global commodity price index across ASEAN+3 countries using the Markov-Switching Vector Error Correction Model (MS-VECM). In contrast to standard MS-VAR models, our MS-VECM framework includes error-correction mechanisms that capture cointegrating relationships among the series. This approach addresses the spurious regression problem highlighted by Granger (1988) while simultaneously modeling both short-run adjustments and long-run equilibrium paths.

The MS-VECM framework also allows for regime-dependent dynamics, where the data are endogenously segmented into distinct states according to a first-order Markov process. This enables the analysis of how short-run adjustments and long-run equilibrium relationships evolve differently across regimes.

In this study, the model is estimated as an MS(2)-VECM(7), meaning that it allows for two regimes and includes seven lags. The analysis is based on the first-differenced series of financial instability and commodity prices, namely DFSI (the difference of the financial stress index) and DLCOMM (the first difference of the logarithm of the global commodity price index). These variables are specified as endogenous, ensuring that the model captures the joint dynamics of financial stress and commodity price fluctuations.

Formally, the model can be expressed as follows:

$$\Delta X_t = \mu(s_t) + \sum_{i=1}^{\rho} A_1(s_t)\,\Delta X_{t-1} + \sum_{j=1}^{\rho} a_1(s_t)\,Z_{t-1} + \varepsilon_t, \varepsilon_t \mid s_t \sim NID\left(0, \Sigma_{s_t}\right) \tag{3}$$

where $X_t = (DFSI_t, DLCOMM_t)$, $s_t \in \{1,2\}$ denotes the unobserved regime at time t, $\mu(s_t)$ represents regime-dependent intercepts, $A_1(s_t)$ is the autoregressive coefficient matrix for lag one, and $\alpha(s_t)$ captures the regime-specific speed of error-correction toward the long-run cointegrating relationship. The error term ε_t follows a normal distribution with variance–covariance matrix Σ_{s_t}.

The transition between regimes is governed by a first-order Markov chain with transition probabilities:

$$Pr(s_t = 1|s_{t-1} = i) = p_{ij}, \sum_{j=1}^{2} p_{ij} \tag{4}$$

This specification ensures that both the short-run dynamics (through differenced terms) and the long-run equilibrium (through the cointegration error-correction term) are explicitly incorporated, while allowing for regime-dependent heterogeneity. The estimation of the MS(2)-VECM(7) is carried out using the Ox program with the MS-VAR package (Krolzig, 1997; 1998), applying the expectation–maximization (EM) algorithm of Hamilton (1989).

Therefore, the MS-VECM provides a flexible and robust framework for analyzing the interaction between financial instability and global commodity prices in ASEAN+3 economies under different market regimes.

4. Experimental Findings

4. 1 Examining the Variables' Stationary

Before estimating the MS-VECM model, it is essential to examine the stationary of the variables in time series analysis, as using non-stationary data can lead to spurious regression and misleading results. In the framework of the nonlinear vector error correction model, all variables must be stationary; otherwise, they should be transformed into a stationary form through first differencing.

To ensure the robustness of the results, the stationary of the variables was examined using four complementary tests: the Augmented Dickey–Fuller (ADF) test, the Phillips–Perron (PP) test, the Unit Root Test with Structural Break, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The results of these tests are reported in Table 1.

The results of the unit root tests indicate that the Financial Stress Index (FSI) is stationary at the level according to the ADF, PP, and KPSS tests. However, it is found to be non-stationary when assessed using the Unit Root Test with Structural Break. In contrast, the logarithm of global commodity prices (LCOMM) is non-stationary according to all four tests. After first differencing, both variables (DFSI and DLCOMM) become stationary, suggesting that they are integrated of order one, I(1).

Table 1. The results of the stationary test of the variables

Variable	the augmented Dickey-Fuller (ADF) test		Unit Root with Break Test		Phillips-Perron Test		Kwiatkowski-Phillips-Schmidt-Shin test statistic	
	T-statistic	P-Value	T-statistic	P-Value	T-statistic	P-Value	LM-Stat Null Hypothesis: variable is stationary 5% Critical Value=0.463	
FSI	-3.7148	0.0004	-3.710	0.1305	-3.6097	0.006	LM-Stat=0.38159	LM-Stat<0.463level %5
LCOMM	-1.6184	0.472	-3.5231	0.3742	-1.5834	0.490	LM-Stat=1.460559	LM-Stat>0.463level %5
DFSI	-	-	-15.540	<0.01	-	-	-	-
DLCOMM	-13.1374	0.000	-13.9948	<0.01	-13.1683	0.000	LM-Stat=0.058906	LM-Stat<0.463level %5

Source: Research calculations and findings

Accordingly, to maintain methodological consistency, the first-differenced variables—DFSI (the difference of the Financial Stress Index) and DLCOMM (the first difference of the logarithm of global commodity prices)—were included in the MS-VECM model.

4.2 Johanson Cointegration Test

The cointegration vectors are identified using the Johansen–Juselius multivariate cointegration technique, since both variables in the model are integrated of the same order (i.e., I(1)). Based on the optimal lag length of 7 for the vector autoregression model, the trace test was employed to determine the number of cointegration vectors.

The results of the trace test, reported in Table 2, reject the null hypothesis of no cointegration at the 5% significance level. These findings confirm the presence of two cointegration vectors among the model's variables, indicating a long-run equilibrium relationship between financial instability and global commodity prices.

Table 2. Test of the number of cointegration vectors

p-r	r	Eigenvec	Trace	Trace^	Crit 5%	p-value	p-value^
2	0	0.4362	81.96	80.78	25.73	0.000	0.000
1	1	0.3286	33.35	33.05	12.45	0.000	0.000

Source: Research calculations and findings

4.3 MS-VECM Model Estimation

4.3.1. Lag Length Selection

Prior to specifying the MS-VECM model, it is necessary to determine the optimal number of lags and regimes. In the context of the MS-VECM specification, the model with the lowest Akaike Information Criterion (AIC) value is considered optimal. The intercepts and autoregressive coefficients of the model are regime-dependent. Furthermore, lag 7 is identified as the optimal lag for the MS-VECM model, as other lag specifications fail to ensure regime stability or variable significance. The results for selecting the optimal lag using the Akaike criterion are presented in Table 3.

Table 3. Akaike statistic to determine the optimal lag

Akaike criterion (AIC)	Number of lags
-1.7942	1
-1.8076	2
-1.8290	3
-1.8621	4
-1.8549	5
-1.8635	6
-1.9066*	7

Source: Research calculations and findings

Based on the results presented in Table 3, lag 7, which exhibits the lowest Akaike value, is selected as the optimal lag for the MS-VECM model.

Table 4. Estimation results of MS(2)-VECM(7) model

Model 1: Dependent variable: commodity price index difference (DFSI)									
Regime 1					Regime 2				
Variable	Coefficient	Std.Error	T-statistic	t-prob	Variable	Coefficient	Std.Error	T-statistic	t-prob
$Constant(0)$	0.0061	0.02154	0.284	0.776	$Constant(1)$	-0.3167	0.1061	-2.99	0.003
$DFSI\_1(0)$	0.1247	0.05515	2.26	0.025	$DFSI\_1(1)$	-0.2563	0.1283	-2.00	0.047
$DFSI\_2(0)$	-0.1056	0.0.5410	-1.95	0.052	$DFSI\_2(1)$	-0.1531	0.1101	-1.39	0.165
$DFSI\_3(0)$	0.1300	0.05029	2.59	0.010	$DFSI\_3(1)$	-0.6690	0.1245	-5.37	0.000
$DFSI\_4(0)$	-0.1176	0.05062	-2.32	0.021	$DFSI\_4(1)$	0.7504	0.1391	5.39	0.000
$DFSI\_5(0)$	0.0308	0.05164	0.598	0.550	$DFSI\_5(1)$	-0.2462	0.1163	-2.12	0.035
$DFSI\_6(0)$	-0.0334	0.05063	-0.661	0.509	$DFSI\_6(1)$	-0.2030	0.1290	-1.57	0.117
$DFSI\_7(0)$	0.0969	0.05290	1.83	0.068	$DFSI\_7(1)$	-0.9038	0.1579	-5.72	0.000
$DLCOMM\_1(0)$	0.8992	0.4612	1.95	0.052	$DLCOMM\_1(1)$	-2.547	1.456	-1.75	0.081
$DLCOMM\_2(0)$	-0.2785	0.4329	-0.643	0.521	$DLCOMM\_2(1)$	-1.4806	1.441	-1.03	0.305
$DLCOMM\_3(0)$	0.6812	0.4213	1.62	0.107	$DLCOMM\_3(1)$	-8.4811	2.276	-3.73	0.000
$DLCOMM\_4(0)$	-0.9358	0.4189	-2.23	0.026	$DLCOMM\_4(1)$	9.793	0.1391	4.53	0.000
$DLCOMM\_5(0)$	-0.1287	0.4199	-0.307	0.759	$DLCOMM\_5(1)$	4.787	2.455	1.95	0.052
$DLCOMM\_6(0)$	-0.5424	0.4293	-1.26	0.207	$DLCOMM\_6(1)$	7.9858	2.760	2.89	0.004
$DLCOMM\_7(0)$	0.0816	0.4474	0.183	0.855	$DLCOMM\_7(1)$	5.4497	2.238	2.44	0.016
Model 2: Dependent variable: financial stress index (DLCOMM)									
Regime 1					**Regime 2**				
Variable	**Coefficient**	**Std.Error**	**T-statistic**	**t-prob**	**Variable**	**Coefficient**	**Std.Error**	**T-statistic**	**t-prob**
$Constant(0)$	0.0064	0.002711	2.39	0.017	$Constant(1)$	-0.0375	0.01183	-3.17	0.002
$DFSI\_1(0)$	0.0050	0.006869	0.734	0.464	$DFSI\_1(1)$	-0.0248	0.01454	-1.71	0.089
$DFSI\_2(0)$	0.0081	0.0070095	1.15	0.250	$DFSI\_2(1)$	-0.0057567	0.01318	-0.437	0.663
$DFSI\_3(0)$	0.00209853	0.006254	0.336	0.737	$DFSI\_3(1)$	0.0146213	0.01501	0.974	0.331
$DFSI\_4(0)$	0.00852564	0.006398	1.33	0.184	$DFSI\_4(1)$	-0.0515902	0.016430	-3.05	0.002

Model 2: Dependent variable: financial stress index (DLCOMM)									
Regime 1					Regime 2				
$DFSI\_5(0)$	-0.0005579	0.006430	-0.0868	0.931	$DFSI\_5(1)$	0.0588955	0.01444	4.08	0.000
$DFSI\_6(0)$	0.00270173	0.006209	0.435	0.664	$DFSI\_6(1)$	-0.009918	0.01667	-0.595	0.552
$DFSI\_7(0)$	0.00414616	0.006333	0.655	0.513	$DFSI\_7(1)$	0.0104753	0.01839	0.570	0.569
$DLCOMM\_1(0)$	-0.151049	0.05953	-2.54	0.012	$DLCOMM\_1(1)$	0.210510	0.1651	1.27	0.204
$DLCOMM\_2(0)$	-0.115370	0.05486	-2.10	0.036	$DLCOMM\_2(1)$	0.2114	0.1796	1.18	0.240
$DLCOMM\_3(0)$	-0.0366495	0.05329	-0.688	0.492	$DLCOMM\_3(1)$	-0.0860509	0.2654	-0.324	0.746
$DLCOMM\_4(0)$	0.0456028	0.05269	0.865	0.388	$DLCOMM\_4(1)$	-0.808954	0.2553	-3.17	0.002
$DLCOMM\_5(0)$	-0.0185177	0.05356	-0.346	0.730	$DLCOMM\_5(1)$	0.897	0.2592	3.46	0.001
$DLCOMM\_6(0)$	0.0440106	0.05397	0.815	0.416	$DLCOMM\_6(1)$	-0.223630	0.3115	-0.718	0.473
$DLCOMM\_7(0)$	0.0443195	0.05541	0.800	0.425	$DLCOMM\_7(1)$	-0.488650	0.2346	2.08	0.038
$Linearity\ LR - test\ Chi\char`^2(32) = 2124.80$ [0/0000] $**$									
$approximate\ upperbound$: [0/000] $**$									
log-likelihood 378.650457									
AIC = -1.90668971					SC = -1.15670869				

Other Coefficients	Coefficient	Std. Error
scale[0]	0.356157	0.01458
scale[1]	0.0433018	0.001787
L[1][0]	-0.0290639	0.006832
$(P\_\{0\|0\})$	0.952597	0.01468
$(P\_\{1\|1\})$	0.644193	0.08692

* Indicates the optimal lag and variable used

Source: Research calculations and findings

4.3.2. Estimation results of MS(2)-VECM(7) model

After determining the optimal lag length, the second stage of the analysis involves estimating the MS(2)-VECM(7) model.

As demonstrated in Table 4, the first phase of the $Linearity\ LR-test$ yields a probability value of less than 1%. This value signifies that the relationship between the variables is nonlinear. According to Hamilton, a recession regime is denoted by a negative y-intercept ($Constant$), while a positive y-intercept denotes a boom regime. In both estimated models—with DFSI (financial stress index difference) as the dependent variable in Model 1 and DLCOMM (commodity price index difference) in Model 2—the first regime represents the boom phase. In contrast, the second regime corresponds to the recession phase.

In Model 1, estimated with 7 optimal lags, the lagged global commodity price variable (DLCOMM_7) has a positive effect on financial stress in both regimes. However, this effect is not statistically significant during the boom, while it is both positive and statistically significant during the recession regime.

This pattern indicates that when global commodity prices rise, ASEAN+3 economies—many of which are net importers of raw materials and energy—experience heightened financial stress during downturns. Higher import costs, inflationary pressures, and deteriorating trade balances amplify financial instability in these countries. During booms, however, stronger economic fundamentals and better liquidity conditions mitigate such pressures, rendering the effect insignificant.

The own lag (DFSI_7) also demonstrates regime-dependent behavior: it has a positive but insignificant impact in the boom phase, while demonstrating a negative and significant effect during recessions. This implies a self-correcting mechanism during financial stress in downturns, as policymakers in ASEAN+3 economies often respond with monetary easing, fiscal support, or liquidity injections to restore stability after a financial disturbance.

In Model 2, the lagged financial stress variable (DFSI_7) exhibits a positive but statistically insignificant effect on global commodity price changes in both regimes. This indicates that financial stress in ASEAN+3 has a limited direct short-term influence on global commodity markets. However, the own lag (DLCOMM_7) displays a positive and insignificant impact during the boom phase, but a negative and significant one during recessions. This indicates that past increases in global commodity prices tend to restrain current price growth during global downturns—likely reflecting weaker aggregate demand, reduced investment activity, and corrections in speculative positions.

Overall, the results reveal that the dynamic linkage between financial instability in ASEAN+3 and global commodity prices is nonlinear and asymmetric. During economic booms, both effects are weak and statistically insignificant, while in recessions, the interdependence becomes stronger and significant.

These findings are consistent with theoretical expectations and prior studies (e.g., Hamilton, 1989; Shahbaz et al., 2019; Chen et al., 2023; Kyei et al., 2023), emphasizing that financial stress intensifies in response to external price shocks during recessions. In contrast, in expansionary phases, stronger macroeconomic resilience buffers the system from such volatility.

Table 5. Likelihood of regime switching

Regime	$\boldsymbol{Regime\ 0, t}$ **(firstregime)**	$\boldsymbol{Regime\ 1, t}$ **(second regime)**
$Regime\ 0, t+1$ (first regime)	0.95260	0.35581
$Regime\ 1, t+1$ (second regime)	0.047403	0.64419

Source: Research calculations and findings

4.3.3. The results from the transition probability matrix

The results from the transition probability matrix are presented in Table 5. As demonstrated in the Table, if the system is in Regime 1 (Regime 0 represents the boom regime) at period t (the current period), the probability of remaining in the same regime is 0.95260. In contrast, the probability of switching to Regime 2 (Regime 1 represents the recession regime) is 0.047403. As indicated in the Table, the sum of the transition probabilities equals one.

Furthermore, the results reveal that if the system is in Regime 2 (recession) during period *t*, there is a 0.35581 probability of transitioning to Regime 1 (boom) and a 0.64419 probability of remaining in Regime 2.

Therefore, based on these findings, it can be concluded that Regime 1 (boom) is more stable than Regime 2 (recession), since the probability of remaining in the boom regime (0.95260) is higher than that of remaining in the recession regime (0.64419). Consequently, the first regime (boom) can be considered more persistent and attractive than the second (recession).

Figure 5 depicts the values observed during regime one, the fitted values, and the forecast for a subsequent period. It demonstrates the actual values of the Financial Stress Index difference (DFSI) and the global commodity price difference (DLCOMM)—the dependent variables—represented by the red line. The blue line represents the fitted (or explained) value of the model. When the line representing the fitted values aligns with the actual values, it indicates that the model has adequate explanatory capability. Error terms represent the discrepancy between fitted values and actual values. Single-time-step forecasting, also referred to as forecasting the subsequent period, uses all information available up to period *t-1* to estimate the value observed in period *t*. One distinction between fitted and predicted values for a subsequent period (1-step prediction) is that fitted values are computed using the complete set of information in the sample. Values from 1 to t-1 are used to compute forecasts for the period following the observations.

4.3.4. The normalized probabilities and distribution of observations in Regimes 1 and 2

Figures 6 and 7 illustrate the normalized probabilities and distribution of observations in regimes 1 and 2, respectively. Prior to delving into the charts, it is prudent to briefly discuss the potential results. In reality, the Markov switching model is a generalization of a structural failure model and differs from it in several ways. Structural failure models employ virtual variables to induce modifications in the model's structure. To illustrate, if the interrelationships among variables change over the war period, it is possible to create a virtual variable that takes the value 1 during those periods and 0 otherwise. This virtual variable can then be incorporated into the model by adjusting the y-intercept or modifying the explanatory variable's coefficients. In structural failure models, regimes are, in fact, exogenously divided. For instance, the aforementioned example designates the period of war as Regime 1, while all other periods are categorized as Regime 2. Utilizing structural failure models is challenging due to their inherent limitations. Firstly, exogenous regime separation is required. Secondly, there is a restriction on the number of breakpoints that can be specified.

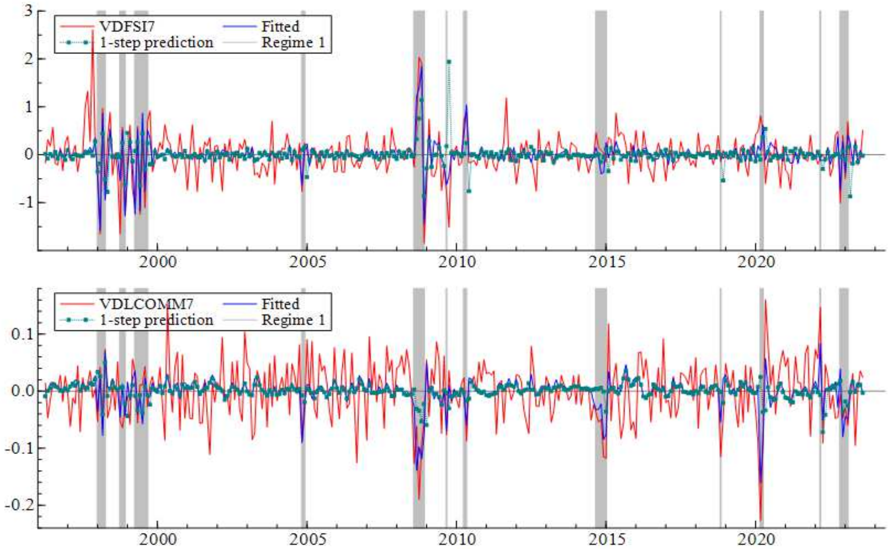

Fig 5. Actual values, fitted values, a forecast for 1-step prediction, and observations assigned to Regime 2 in accordance with the estimation results of the MS (2)-VAR (7) model

Source: Research calculations and findings

In contrast to structural failure models, regimes are distinguished endogenously and utilize probabilities in the Markov model. As stated in the

Markov switching model, it also imposes no limit on the number of breakpoints. Moreover, the differentiation of observations into regimes is achieved endogenously. The process of dividing observations into regimes consists of two stages: filtering and smoothing. Filtering, a form of data preprocessing, is performed before addressing the likelihood function or the model estimation problem. Smoothing is performed concurrently with the solution of the likelihood function. The primary distinction between the smoothing and filtering stages is that, in the filtering stage, information available up to period *t*, or sample observations 1 to t, is used to compute the probability that the given observation at period *t* belongs to Regime 1 or 2. The smoothed probabilities are calculated from all probabilities in the sample. However, the main goal during the filtering and smoothing phases is to assess the likelihood that observation *t* belongs to Regime 1 and to Regime 2. The Markov switching model utilizes smoothed probabilities to partition observations between regimes. Considering the increased probability that observation *t* could be in any of the regimes, it is accordingly designated to that regime.

Contrary to structural failure models, which treat the war period as an exogenous variable, the Markov switching model endogenously partitions regimes based on probabilities and the data's structure. Figure 6 illustrates the observations belonging to Regime 1, denoted as Regime 0, which corresponds to the boom phase. Conversely, Figure 7 presents the observations belonging to Regime 2, denoted as Regime 1, which signifies the recession regime. In these diagrams, the red lines correspond to the smoothed probabilities. Figure 6 demonstrates that the first observation is in Regime 1 with probability 0.89158 and in Regime 2 with probability 0.10842, facilitating understanding of the smoothed probabilities. The sum of these probabilities should equal 1; this can be attributed to observations or other factors in Regimes 1 and 2. Therefore, the overall probability of being in either of these two regimes is one. As previously stated, the observation will be attributed to the regime with the higher calculated probability. Given that the probability of being assigned to Regime 1 is 0.89158, the first observation of the sample will inevitably be assigned to Regime 1. The presence of blue areas delineating the first observation and subsequent observations within this regime is illustrated in Figure 6. As depicted in Figure 7, the gray color signifies observations that are within Regime 2.

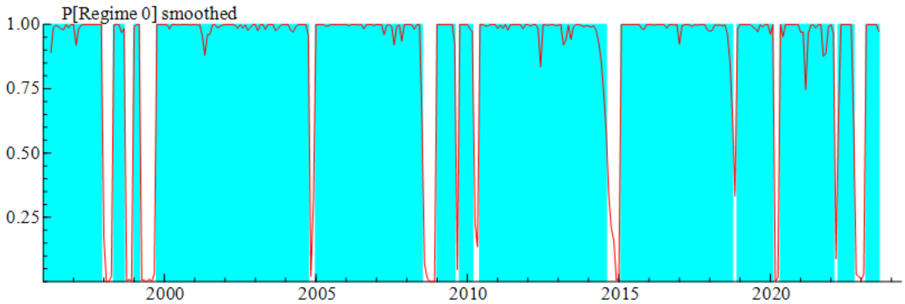

Fig 6. The years associated with the probability of being in the first regime, as estimated by the MS (2)-VECM (7) model

Source: Research calculations and findings

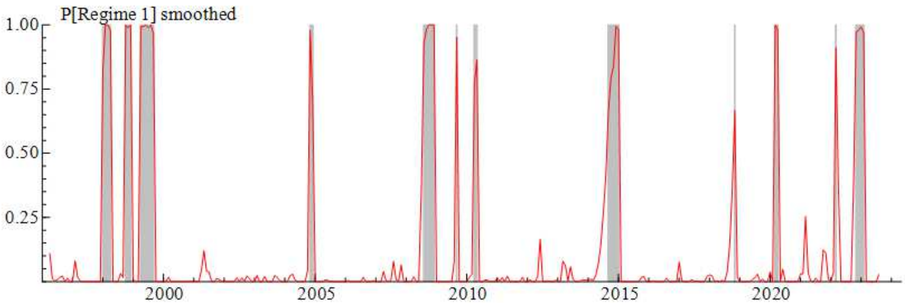

Fig 7. The years associated with the probability of being in the second regime, as estimated by the MS (2)-VECM (7) model

Source: Research calculations and findings

4.4.5. Regime characteristics in MS(2)-VECM(7) Model

According to the estimation results of the MSIA(2)-VECM(7) model, the characteristics of each regime are presented in Table 6. The results in Table 6 indicate that the average duration in Regime 0 is approximately 22.54 years, while in Regime 1 it is 3 years. Moreover, the probability of being in Regime 0 is about 89.06%, whereas the probability of being in Regime 1 is 10.94%. Therefore, the probability of remaining in Regime 0 is more than eight times higher than that of Regime 1.

Table 6. Regime characteristics in MS(2)-VECM(7) Model

Number of observations (months)	Probability	average duration	Regime
293	89.06%	22.54	0
36	10.94%	3	1

Source: Research calculations and findings

4.4.6. Results of the causal relationship test

As illustrated in Table 7, the causal relationships between the differences of the global commodity price index (DLCOMM) and the Financial Stress Index (DFSI) exhibit different behaviors across the two regimes.

The results in Table 7 reveal that during the second regime (recession), a two-way nonlinear causal relationship exists between DLCOMM and DFSI. This indicates a mutual feedback mechanism between commodity price fluctuations and financial stress during financial crises. In other words, changes in global commodity prices can amplify financial instability. In contrast, financial stress shocks can affect commodity price dynamics by influencing production costs, investment, global demand, and exchange rates. A decline in global commodity prices during recessions can lead to reduced export revenues, weakened fiscal balances, and increased default risks in commodity-dependent countries. Conversely, heightened financial stress can disrupt supply and demand by constraining financing and reducing market liquidity, thereby increasing price volatility. Furthermore, the lags of DFSI in this regime serve as the Granger cause of DFSI itself, while the lags of DLCOMM also Granger-cause DLCOMM, reflecting self-reinforcing effects and greater persistence during recessions.

In contrast, in the first regime (boom), a one-way non-linear causal relationship from DLCOMM to DFSI is observed at the 10% significance level (p = 0.0548). This indicates that during periods of economic expansion, fluctuations in global commodity prices can partially explain changes in the financial stress index of ASEAN+3 countries. In such periods, rising commodity prices are generally associated with improved economic conditions and export growth, which can reduce financial pressures. However, because this effect is unidirectional, changes in financial instability during booms do not significantly affect commodity prices, and the lags of DLCOMM in this regime do not Granger-cause DLCOMM. Meanwhile, the lags of DFSI still Granger-cause DFSI, indicating the autoregressive nature and persistence of financial stress dynamics.

Overall, the results confirm the presence of non-linear, regime-dependent causality between global commodity price fluctuations and financial stress, indicating that the strength and direction of causality differ between boom and recession periods. These findings are consistent with theoretical expectations and the results of Chen et al. (2023) and emphasize the importance of considering regime-dependent behavior when analyzing financial and commodity market dynamics in East Asian and ASEAN+3 economies.

4.4.7. Model Diagnostics: Autocorrelation and Heteroskedasticity Tests

To assess the adequacy of the estimated MS-VECM model, diagnostic tests were conducted for serial correlation and residual heteroskedasticity. Diagnostic checks confirm the adequacy of our estimated model. The Vector Portmanteau test yields p-values above 0.05 for both raw and squared residuals, indicating no serial correlation or ARCH effects in the residuals.

Similarly, the Vector ARCH test reveals that the null hypothesis of no autoregressive conditional heteroskedasticity (ARCH effect) cannot be rejected, suggesting the absence of conditional heteroskedasticity in the residuals. These results confirm that the model residuals are well-behaved and that the specification is appropriate.

Table 7. Results of the causal relationship test (LinRes Chi²(7) and p-value)

Independent variable / Dependent variable	Regime 1		Regime 2	
	DFSI	**DLCOMM**	**DFSI**	**DLCOMM**
DFSI	DFSI→ DFSI 23.2926 (0.0015)	DLCOMM→ DFSI 13.8035 (0.0548)	DFSI→ DFSI 141.059 (0.0000)	DLCOMM→ DFSI 99.546 (0.0000)
DLCOMM	DFSI≠ DLCOMM 3.95499 (0.7849)	DLCOMM≠DLCOMM 12.7603 (0.0782)	DFSI→ DLCOMM 25.4287 (0.0006)	DLCOMM→ DLCOMM 34.5004 (0.0000)
Summary	In first regime (regime 0 or boom regime) DFSI→ DFSI DLCOMM→ DFSI DLCOMM≠DLCOMM DFSI≠ DLCOMM		In second regime (regime 1 or recession regime) DFSI→ DFSI DLCOMM↔DFSI DLCOMM→DLCOMM	

The numbers in parentheses indicate the probability value.

Source: Research calculations and findings

Table 7. Diagnostic Tests for Serial Correlation and Heteroskedasticity

Test	Statistic	df	p-value	Conclusion
Vector Portmanteau (36) – Scaled Residuals	Chi^2 (144) = 144.11	144	0.4818	No autocorrelation
Vector Portmanteau (36) – Squared Scaled Residuals	Chi^2 (144) = 131.92	144	0.7559	No autocorrelation in squared residuals
Vector ARCH 1–1 Test	F(4,520) = 0.6297	4	0.6415	No conditional heteroskedasticity

Source: Research calculations and findings

5. Conclusion and Recommendations

Our analysis explores the time-varying, nonlinear linkages between financial stress and global commodity prices across ASEAN+3 economies from 1995:1 to 2023:8. Using a Markov-switching VECM framework, we identify distinct behavioral patterns across boom and recession regimes. The causality analysis revealed that in the recession regime (Regime 1), a two-way nonlinear causal relationship exists between DFSI and DLCOMM. This indicates a mutual feedback mechanism, in which increases in commodity price volatility exacerbate financial stress. Additionally, shocks in financial stress affect production costs, investment, global demand, and exchange rates, which, in turn, influence commodity prices. Lags of DFSI and DLCOMM in this regime Granger-cause themselves, reflecting strong persistence and self-reinforcing effects during financial distress. In contrast, in the boom regime (Regime 0), a one-way nonlinear causal relationship from DLCOMM to DFSI was observed at the 10% significance level ($p = 0.0548$), while the feedback from DFSI to DLCOMM was not significant. Only DFSI's lags Granger-cause DFSI, indicating autoregressive stability, whereas DLCOMM's lags do not Granger-cause DLCOMM, indicating stable commodity price dynamics during booms.

The regime transition probability analysis indicates that the boom regime is more stable and persistent than the recession regime, highlighting the importance of distinguishing policy responses according to economic phases. These findings provide a clear, quantitative basis for targeted policy interventions. During recessions, the two-way causal link implies that financial stress amplifies the effects of commodity price shocks, suggesting that policymakers should prioritize interventions that stabilize financial conditions and mitigate the transmission of external price fluctuations. Specifically, empirical results indicate that during periods of high financial stress, controlling liquidity, providing timely credit support to critical sectors, and stabilizing exchange rates can reduce feedback effects on commodity prices. Additionally, the strong persistence of DFSI underlines the importance of preemptive monitoring of financial stress indicators to implement corrective measures before shocks escalate.

During boom periods, as the causal relationship is primarily from commodity prices to DFSI, policy measures can focus on monitoring commodity market volatility and maintaining macroeconomic stability to prevent excessive stress in financial markets. For example, measures could include strengthening risk management frameworks for financial institutions exposed to commodity price fluctuations and supporting industries particularly sensitive to global commodity prices.

This study emphasizes that effective policy in ASEAN+3 economies must be regime-specific and evidence-based, directly linked to quantitative results from the MS-VECM analysis. By tailoring interventions according to the identified causal patterns, policymakers can enhance financial stability, reduce the amplification of shocks through feedback mechanisms, and support sustainable economic growth. These findings also highlight the importance of systematic monitoring of DFSI and DLCOMM to design timely and targeted economic and financial policies.

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Authors' contributions

All authors had contribution in preparing this paper.

Conflicts of interest

The authors declare no conflict of interest

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