

Nonlinear Dependence and Dynamic Interactions Between LAK per USD and LAK per THB Exchange Rates: A Wavelet and Quantile Cross-Spectral Analysis

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Abstract

This study analyzes the intricate linkages and dynamic interactions between the Lao Kip (LAK), U.S. Dollar (USD), and Thai Baht (THB) exchange rates from January 1990 to February 2024, utilizing wavelet coherence and quantile cross-spectral analysis. This research identifies significant interconnectedness and co-movement patterns by evaluating interconnections in both temporal and frequency domains, thus addressing a crucial gap in the context of Laos. A quantile coherency study indicates robust synchronization at the 0.95 quantile amid extreme market conditions, with coherency values above 0.6 at lower frequencies, although weaker yet positive correlations (0.2-0.4) are noted at the 0.05 quantile. Wavelet coherence analysis reveals intervals of intensified co-movement throughout the Asian Financial Crisis (1997-2003) and the COVID-19 pandemic (2020-2024), emphasizing long-term cycles ranging from 16 to 64 months. Cross-wavelet power analysis verifies the preeminence of the LAK/USD exchange rate, which often precedes the LAK/THB, highlighting the systemic significance of the U.S. dollar. The findings indicate the Lao economy's susceptibility to exogenous shocks over different time frames and emphasize the necessity for synchronized monetary policy and strong hedging strategies.

Keywords: Quantile Coherency, Wavelet, Systematic Risk, Exchange Rate, Laos, Co-movement, Kip

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1. Introduction

The interactions between exchange rate co-movement and independence have attracted significant attention from researchers, policymakers, and financial professionals because of their wide-ranging consequences for international trade, investment strategies, and monetary stability especially for Lao PDR in recent years. Grasping these dynamics is crucial for formulating effective macroeconomic policies and establishing robust risk management frameworks. Throughout the years, researchers have explored the phenomenon of exchange rate co-movement through various lenses, such as returns (Nikkinen et al., 2010; Brooks & Del, 2006), volatility spillovers (Lin et al., 1994; Arouri et al., 2011), and macroeconomic linkages (Ramsey & Zhang, 1996). These approaches often overlook time-frequency heterogeneity, the possibility that exchange rate interdependencies vary across short, medium, and long-term horizons. This gap is critical for Laos, where the Lao Kip (LAK) faces dual pressures from the Thai Baht (THB) and U.S. Dollar (USD), yet existing literature relies on linear models (Kyophilavong et al., 2018; Xaiyavong & Toyoda, 2016) that cannot disentangle hierarchical dependencies.

The Lao Kip (LAK) is intricately linked to the U.S. Dollar (USD) and Thai Baht (THB), providing a unique lens for analyzing exchange rate dynamics in a small, open economy. Laos's economic dependency on Thailand spans decades, rooted in geographic proximity, shared borders, and asymmetrical trade relations. Since the 1980s, Thailand has emerged as Laos's primary investor, particularly in infrastructure (e.g., hydropower dams, highways) and agriculture (Kyophilavong & Toyoda, 2008), with cumulative Thai FDI exceeding USD 5 billion as of 2023 (Bank of Thailand, 2024). Laos operates as a highly dollarized, transitional economy where foreign currencies most notably the Thai Baht and the US Dollar are widely substituted for the domestic kip to serve as a means of payment, unit of account, and store of value. This multiple-currency phenomenon is deeply entrenched in the Lao financial system, with foreign currency deposits historically making up around 50% of total bank deposits in the country (Kyophilavong et al., 2019). The THB's dominance is further reinforced by Laos's reliance on Thai imports, such as fuel, machinery, and consumer goods, which accounted for 51% of total imports (USD 336 million) in April 2024 (Department of Customs, Lao PDR, 2024). Conversely, Laos exports raw materials (e.g., copper, gold, cassava, and electricity) to Thailand, often priced in USD, creating a dual dependency where LAK stability hinges on both regional (THB) and global (USD) forces.

The LAK's vulnerability is compounded by deep structural imbalances. For instance, with nearly 280,000 documented Laotian workers employed in Thailand (International Labour Organization (ILO), 2024), financial remittances serve as a crucial economic lifeline. While formal remittances exceed USD 287 million annually, substantial informal transfers push the aggregate amount much higher (World Bank, 2024). Because these funds flow into the country predominantly in THB and largely bypass the formal banking sector, they sustain rural households but simultaneously entrench currency substitution, starving the central bank of foreign exchange and exacerbating LAK depreciation pressures during economic downturns. Similarly, Thai investors in Laos's mining and energy sectors repatriate profits in THB, amplifying demand for the currency. These entrenched linkages mean Thailand's monetary policy decisions, such as interest rate adjustments by the Bank of Thailand, have direct spillover effects on the LAK. For example, during Thailand's post-1997 recovery, tighter monetary policies strengthened the THB, indirectly straining the LAK and triggering a catastrophic

86.97% depreciation against the USD and 80.25% against the THB between 1996 and 1999 (Bank of the Lao PDR, 2024).

Laos has encountered persistent difficulties sustaining currency stability, with the LAK depreciating at an average annual rate of 9.7% against the THB and 10.5% against the USD from 1990 to 2024, reflecting methodological differences in timeframe selection. These disparities underscore the LAK's chronic fragility, driven by trade deficits, critically low foreign reserves (USD 1.2 billion in 2024), and reliance on volatile commodity exports. As of December 2024, Laos's international liquidity stood at a precarious USD 2.1 billion (Bank of Laos, 2024), a figure dwarfed by Thailand's USD 240 billion reserves, leaving the LAK acutely vulnerable to external shocks.

The COVID-19 pandemic and external shock exacerbated these trends: border closures disrupted cross-border trade, while Thailand's stronger fiscal position enabled the Thai baht (THB) to withstand external shocks more effectively. This divergence caused the LAK/THB exchange rate to surge from 267.43:1 in early 2019 to 636.13:1 by late 2024, a 137.87% depreciation of the Lao kip (LAK). Similarly, the LAK/USD rate plummeted from 8,541.44:1 to 21,707.40:1, reflecting a 154.14% decline over four years. These sharp depreciations doubled import costs for Lao businesses and fueled inflation, which soared to a peak of 26.2% by mid-2024.

The Bank of Lao PDR (BOL) faces an uphill battle in stabilizing the LAK. While measures such as crackdowns on unofficial exchange markets and efforts to promote local currency settlements have provided short-term relief, structural reforms are severely hampered by Laos's massive debt burden, with the public debt-to-GDP ratio projected at 94% in 2024 (International Monetary Fund (IMF), 2024). Furthermore, with international liquidity sitting at just USD 2.1 billion equivalent to less than 1% of Thailand's massive foreign exchange reserves the BOL's capacity to actively defend the LAK remains severely constrained. In this context, understanding LAK/THB dynamics is not merely academic; it is a prerequisite for crafting policies that address Laos's systemic vulnerabilities while navigating its profound and asymmetrical interdependence with both Thailand and the USD.

The investigation into the LAK has yielded significant understanding of its weaknesses and relationships. Toyoda & Kyophilavong (2009) identified a directional relationship from LAK/USD to LAK/THB, highlighting the role of the USD in influencing regional currency dynamics. However, recent trends suggest a growing asymmetry: while USD remains dominant in macro-level transactions (e.g., energy imports), THB's influence on LAK has intensified due to deepening regional integration under ASEAN economic agreements and Laos's reliance on Thai agricultural and goods exports (ASEAN Secretariat, 2022). Kyophilavong et al. (2018) conducted an analysis of the influence of exchange rate stability on Laos's trade balance with Thailand, whereas Xaiyavong & Toyoda (2016) investigated the external factors contributing to the volatility of the Lao Kip. While these studies provide valuable insights, they depend on linear models, which may restrict the comprehension of time-varying and frequency-specific attributes in currency relationships.

Exchange rate dynamics have long been studied using a variety of econometric techniques, such as GARCH models (Lin et al., 1994), cointegration techniques (Dias & Embrechts, 2010), and correlation analysis (Brooks & Del, 2006). Through the identification of important links and patterns, these models have significantly advanced our understanding of currency behavior. Recently, researchers have investigated nonlinear approaches, including delay vector variance and copula-based models, aimed at capturing complex dependencies that may emerge during times of economic instability (Bekiros, 2014). Although each approach possesses distinct advantages, there is an

ongoing requirement for methodologies that can analyze relationships over various time frames, especially within the context of emerging markets.

Wavelet analysis has developed into a valuable method for examining multiscale co-movement, providing the capability to concurrently assess short-term fluctuations alongside long-term trends. Wavelet techniques offer a detailed perspective on the changing dynamics among currencies by decomposing time series data into frequency-specific components. Instruments like wavelet coherence and wavelet multiple correlation (WMC) have been employed to investigate time-frequency dependencies among key currencies, uncovering dynamic lead-lag relationships and their evolution over time (Aguiar-Conraria & Soares, 2011). Furthermore, wavelet methods have revealed the impacts of global financial crises, including the Global Financial Crisis and the European Debt Crisis, on currency interdependencies in advanced economies (Yang et al., 2016; Nikkinen et al., 2011).

Commercial banks interact with currency markets throughout a range of time periods, from short-term speculators to long-term investors. Comprehending the weekly, monthly, and yearly co-movement of currency rates is essential for formulating successful investment and monetary policy plans for the Bank of the Lao PDR. A thorough grasp of hierarchical currency dynamics is made possible by wavelet analysis, which offers a distinct benefit by breaking down time series into components that represent various frequencies (Addo et al., 2013). We hypothesize that the LAK/USD exchange rate systematically leads the LAK/THB rate across short-, medium-, and long-term horizons, driven by Laos's immediate USD outflows for critical imports (e.g., oil) and the delayed transmission of THB inflows from exports to Thailand (e.g., electricity), which are subject to contractual pricing lags and Thailand's monetary policy spillovers. Examining the relationship between LAK/USD and LAK/THB exchange rates using wavelet analysis presents a significant opportunity to address current gaps in the literature and extract practical insights for Laos and its regional trade partners.

The approaches give a robust framework for discovering linkages that alter over time and vary by frequency, providing deeper currency co-movement insights. These methods are used in this study to better understand exchange rate movements in emerging economies. The findings could help policymakers and financial stakeholders address systemic risks and boost economic resilience and stability.

2. Literature Review

The co-movement of exchange rates has been the subject of extensive research, as it is crucial for understanding trade balances, investment strategies, and monetary stability. Researchers have employed a diverse array of methodologies to investigate these dynamics over time, each contributing to the understanding of currency interdependencies and their broader economic implications. This section analyzes these methodologies, placing particular emphasis on traditional econometric approaches prior to transitioning to modern techniques that explore nonlinear and multiscale dynamics. Special attention is given to gaps in the study of small, open economies like Laos, where structural dependencies on dominant regional currencies (e.g., Thai baht) and nonlinear dynamics are critical yet underexplored.

Preliminary inquiries into exchange rate relationships primarily employed linear econometric models, which were instrumental in revealing substantial dependencies and volatility patterns. Correlation analysis and cointegration techniques have demonstrated considerable efficacy as methodologies. Brooks & Del (2006) employed correlation measures to assess the degree of co-movement between stock returns and exchange rates,

emphasizing the importance of external disruptions in influencing currency relationships. In a comparable context, Dias & Embrechts (2010) utilized cointegration techniques to examine the interdependencies between EUR/USD and JPY/USD, revealing long-term equilibrium relationships that exhibit variability during periods of economic turmoil. However, such models often overlook asymmetries inherent in small economies, where currency dynamics are disproportionately influenced by a dominant neighbor (e.g., THB's role in Laos).

A traditional approach encompasses GARCH models, which have been extensively employed to examine volatility spillovers. Lin et al. (1994) employed these models to analyze the USD/JPY and GBP/USD currency pairs, uncovering significant clustering effects and interdependencies between the respective markets. The analysis demonstrated the cross-border transmission of exchange rate volatility, underscoring the importance of market integration. The research established a solid foundation for understanding currency dynamics; however, it often faced difficulties in precisely depicting time-varying relationships and nonlinear patterns. While these models illuminated dependencies in advanced economies, their linear frameworks struggle to capture the asymmetric influences. For instance, Thailand's monetary policy disproportionately impacts the LAK due to trade imbalances and the THB quasi-currency status dynamic linear models often oversimplify. Additionally, such approaches fail to account for time-varying interactions, such as shifting dependencies during crises, which are critical in Laos's context.

Patton (2006) introduced copula-based models, offering a more flexible framework for the examination of dependencies. His examination of the United States dollar and the Deutsche mark revealed asymmetric dependencies, particularly during periods of currency depreciation. The efficacy of these models in overcoming specific limitations of prior methodologies is apparent, particularly in their capacity to discern shifts in interdependence during times of economic volatility.

Bekiros & Diks (2008) analyzed six major currency pairs (EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD) from 1991 to 2007. Using GARCH-BEKK filtering to control volatility spillovers and the Diks-Panchenko nonparametric test, they identified persistent nonlinear causal linkages post-crisis. Notably, EUR/USD exhibited spillover effects on other currencies, driven by asymmetries and higher-order moments, highlighting nonlinear interdependencies beyond linear models.

Bekiros (2014) advanced this research by utilizing copula models to analyze the multivariate relationships among principal currencies. He observed that nonlinear models often exhibit enhanced performance relative to linear models, especially in volatile market conditions. The findings suggest that nonlinearity and asymmetry are pivotal in understanding the behavior of exchange rates in reaction to external disruptions.

Loaiza-Maya et al. (2015) employed a regional methodology, utilizing copula techniques to examine currency contagion within Latin America. The analysis elucidated the mechanisms through which disruptions in major markets propagate to smaller economies, underscoring the vulnerabilities intrinsic to interconnected financial systems. Their research provided substantial insights into the influence of global financial cycles on regional currencies, with a particular emphasis on emerging markets.

Wavelet analysis has evolved from earlier methodologies into a sophisticated tool for examining multiscale co-movement within currency markets. This methodology allows researchers to concurrently analyze short-term fluctuations and long-term trends, thereby augmenting their efficacy in discerning time-varying relationships. Aguiar-Conraria & Soares (2011) employed wavelet coherence to examine the synchronization of business cycles within the Eurozone, demonstrating that the co-movement of currencies displayed significant variability across various temporal horizons.

Kumar et al. (2017) employed wavelet analysis to investigate Asian markets, with a particular focus on the futures of USD/INR, EUR/INR, GBP/INR, and JPY/INR. The analysis indicated that economic crises, such as the Global Financial Crisis, exacerbated co-movement at lower frequencies, implying a heightened presence of long-term dependencies during periods of market distress. It was noted that short-term fluctuations became markedly more pronounced during intervals characterized by speculative trading activities. Their research demonstrates the versatility of wavelet methodologies in elucidating relationships that are contingent upon both scale and temporal factors.

Yang et al. (2016) utilized wavelet methodologies to examine the GBP/USD, EUR/USD, and JPY/USD currency pairs within the framework of the European Debt Crisis. The analysis uncovered dynamic lead-lag relationships among these currencies, suggesting that interdependencies became more pronounced during periods of crisis. Their findings underscore the importance of time-frequency methodologies in examining the impact of economic disruptions on currency markets.

Fernández-Macho (2012) introduced wavelet multiple correlation (WMC), a methodology that enables the analysis of multivariate currency systems. He elucidated the hierarchical relationships among currencies, designating certain currencies as leaders while categorizing others as followers across multiple temporal scales. His research has made substantial contributions to the analysis of the interrelations among global financial markets, offering critical insights into the systemic risks linked to currency dependencies.

Emerging market currencies, especially those in Southeast Asia, present unique challenges and opportunities for the examination of exchange rates. Nusair (2012) employed a nonlinear Autoregressive Distributed Lag (ARDL) methodology to examine the currencies of the ASEAN region, demonstrating the influence of exogenous shocks, such as variations in oil prices, on the interdependencies among these currencies. He emphasized the importance of trade and investment linkages in shaping these relationships.

Toyoda & Kyophilavong (2009) investigated the correlation between the Lao Kip (LAK) and both the United States Dollar (USD) and the Thai Baht (THB), uncovering a directional causality from LAK/USD to LAK/THB. Their findings highlighted the substantial impact of the United States Dollar (USD) on the dynamics of regional currencies. Kyophilavong et al. (2018) conducted an analysis of the impact of exchange rate stability on the trade balance between Laos and Thailand, while Xaiyavong & Toyoda (2016) explored the external factors that contribute to currency volatility. These studies underscore the importance of examining minor economies within the context of the broader regional and global framework.

Although considerable progress has been achieved in understanding the co-movement of exchange rates, there remain significant deficiencies, particularly in relation to multiscale and nonlinear dynamics within minor economies. Previous methodologies provided valuable insights; however, they often lacked the ability to effectively capture relationships that fluctuate over time and across various dimensions.

Table 1: Literature Review

No	Author(s)	Data	Methodology	Variables	Finding
1	Aguiar- Conraria et a. (2008)	1950-2000	Wavelet	Interest rate to Inflation, Industry Production, M2, M1	In the 1970s and 1980s, inflation and interest rates aligned at business cycle frequency, with inflation rates leading. Long-term, 12–20 years
2	Aloui & Hkiri (2014)	6/7/2005 to 22/2/2010	Wavelet	Stock Market	In Bahrain and Kuwait, the dynamic correlation between stock markets is high (>0.8) and frequent (>217 days), and co-movement patterns among GCC markets
3	Baharumshah et al. (2010)	1965: Q1 to 2004: Q2	ESTAR and logistic STAR	IDR/USD, KRW/USD, MYR/USD, PHP/USD, SGD/USD, THB/USD	There are nonlinearities in the Asian RERs; asymmetric adjustment in RERs can lead to nonlinear adjustment in real interest rate parity.
4	Boero et al. (2011)	January 1994 to November 2007	Copula	DM(Euro)/USD to BP/USD, SF/USD, and JY/USD	Significant evidence that EUR/USD-BP/USD 21 has been associated with rising strength post-euro and with stronger dependency during depreciations than appreciations; EUR/USD-SF/USD co-movements are more persuasive.
5	Chu (2017)	04/1/1999 to 31/12/2016	MF-DFA	EUR/USD, EUR/YEN, EUR/POUND, EUR/RAND	The Euro exchange rate moves with high fluctuation and displays an unstable status. The Euro is not strong but easily influenced by financial shocks. The Global Financial Crisis caused very deep and long-term damage to the EU economy.
6	Dias & Embrechts (2010)	1/10/2000 to 1/10/2008	Copula-GARCH	EUR/USD, Yen/USD	high significance at all time horizons. decrease in the dependence between the EUR/USD and JPY/USD returns during the first three quarters of 2007, followed by an increase till mid-2008 back to values observed before 2007
7	Bekiros & Diks (2008)	3/20/1991 to 3/20/2007	GARCH-BEKK	EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD and USD/CAD	EUR/USD cause another currency acts as a spillover, there is a nonlinear relationship.

No	Author(s)	Data	Methodology	Variables	Finding
8	Feng et al. (2010)	1/7/1997 to 7/8/2009	Cross sample entropy and cross entropy	Yen and Asian Countries	The dependence upon the US dollar has been weakened, which has been proved by evaluating the correlation coefficient matrix, the cross-sample entropy, and the cross entropy.
9	Gallegati (2012)	3/7/2003 to 19/12/2008	Wavelet-based	S&P 500, S&P TSX, NIKKEI 225, FTSE 100, CAC 40, DAX 30, FTSE MIB, BVSP, and HSI	Lower scales (higher frequencies) are associated with contagion, and higher scales (lower frequencies) are associated with interdependence.
10	Gomez-Gonzalez & Rojas-Espinosa (2019)	Daily 11/1991 to 3/2017	DCC-GARCH and copula	AUD, HKD, INR, IDR, JPY, MYR, NZD, SGD, KRW, THB, TWD, PHP	A t-copula — or SBB copula — works best. The Japanese yen and New Zealand dollar are the most distant currencies, while the Malaysian ringgit is the network center. Due to increased integration, Asian economies move together.
11	Heni & Mohamed (2011)	1/1/1999 to 31/3/ 2008	GARMA-FIGARCH, Wavelets MODWT	Tunisian currency rates vs USD, EUR, and JPY	G-frequency is near to zero for all three nations, indicating long-term seasonality and supporting the seasonal persistent specification in the mean equation of the filtered exchange rate series. The detrended exchange rate series has more volatility when the fractional parameter is between 0.374 and 0.398.
12	Inagaki (2007)	5/1/1999 to 30/12/2004	Granger	British pound and euro nominal U.S. dollar exchange rates	Britain and the euro interact strongly; the euro Granger-causes the British pound in the mean, but the British pound does not. The euro Granger-causes the British pound in variance, but not vice versa.
13	Kitamura (2010)	28/7/ 2008 to 31/7/2009	VC MV-GARCH	euro, pound, and Swiss franc	(1) Euro return volatility affects the pound and franc. (2) Euro news impacts the pound and Swiss franc simultaneously, and co-movements of these currencies and the euro rise in proportion to euro news.
14	Loaiza-Maya et al. (2015)	6/ 2005 to 4/2012	Regular Vine Copulas	Argentina, Brazil, Chile, Colombia, Mexico, and Peru	Contagion exists among the exchange rate.

No	Author(s)	Data	Methodology	Variables	Finding
15	Nikkinen et al. (2011)	1/10/2001 to 31/12/2007	wavelet cross-correlations (MODWT)	EUR/USD $\leftrightarrow$ GBP/USD EUR/USD $\leftrightarrow$ JPY/USD GBP/USD $\leftrightarrow$ JPY/USD	Lead-lag correlations exist for exchange rate forecast probability densities. GBP/USD and EUR/USD exchange rates are optimistic. EUR/USD and GBP/USD volatility depends on JPY/USD. Short-term volatility expectations favor the JPY in the currency rate triplet.
16	Nikkinen et al. (2006)	2/1/ 2001 to 29/1/ 2003	VAR	Euro, British pound, and Swiss against USD	Market expectations of future exchange rate volatilities are intricately linked among major European currencies.
17	Orlov (2009)	1/ 1996to 1/1998	Cross-spectral	USD to 9 Asian country (China, India, Indonesia, Japan, Malaysia, Philippines, Singapore, S. Korea & Thailand; 2 Latin American: Brazil and Mexico; and EU(German) DM-USD, Yen-USD	Increased high-frequency co-movements. Some nations' high-frequency co-movements rose during the Asian crisis, corroborating our prediction that covariance can shift from low- to high-frequency components during a crisis. Based on high-frequency covariance change, 48 of 66 nation pairs show contagion.
18	Patton (2006)	2/1/1991 to 31/12/ 2001	Copulas, GARCH		higher dependence during depreciation. There is significant evidence that the euro's January 1999 adoption ruptured the conditional copula. After the interruption, exchange rate dependency dropped dramatically, and conditional dependence went from asymmetric to symmetric.
19	Pérez-Rodríguez (2006)	1/1/1999 to 1/3/2004	Correlation (DCC)YGARCH	EUR/USD, GBP/USD, JPY/USD	The euro, Yen, and British pound have volatility spillovers, a significant correlation with the U.S. dollar, a strong link between the ECB euro reference rate and U.S. spot rates, and a rapid decrease in volatility after new EU member states join.
20	Ramsey & Zhang (1997)	1/10/1992 to 30/9/1993	Waveform dictionaries	Yen and Deutsche Mark against U.S. dollar and Deutsche Mark vs. Yen	Long-term, the distribution of initial differences remains centered at zero. Neither the unconditional variance nor

No	Author(s)	Data	Methodology	Variables	Finding
21	Rua & Nunes (2009)	1/1973 to 12/2007 total 420 months	Wavelets	Stock market	the standardized fourth moment shows excessive variation. International variety may not benefit long-term since stock market co-movements are higher but less frequent. After the nineties, co-movement increased slowly at lower frequencies and swiftly at others.
22	Tamakoshi & Hamori (2014)	1/1/1999 to 31/12/2010	GARCH	USD in EUR, GBP, and CHF.	Analysis showed that the three exchange returns were more interdependent during appreciation than depreciation vs. the USD. Second, the CHF–EUR dynamic correlation dropped significantly.
23	Yang et al. (2016)	1/12002 to 31/12/ 2013	Wavelet	GBP/USD, EUR/USD, and JPY/USD	Contagion between the euro, yen, and pound is evident in global foreign exchange markets. Significant pound-euro and euro-yen reliance across all timeframes. perceive limited long-term yen-pound dependency. Before 2006, the pound led the yen mid-term, while other pairs paralleled. Interest rate parity predicts long-term yen-euro and pound-euro exchange rates, but not yen-pound.
24	Kumar et al. (2027)	1/2/2010 to 26/8/2014	wavelet	USD/INR, EUR/INR, GBP/INR, JPY/INR	Co-movement of EUR and USD is strong at lower frequencies. Co-movement of GBP and EUR is significant at both high and low frequencies.

Source: Author's compilation based on literature.

3. Empirical Methodology and Data

3.1 Data

To investigate the nonlinear dependence and systemic risk between the LAK/USD and LAK/THB exchange rates, we obtained monthly exchange rate indices from the Bank of Laos. The sample period spans from January 1990 to February 2024. Descriptive statistics for the series, summarized in Table 2, reveal evidence of asymmetry, fat tails, and high peaks, as indicated by skewness and kurtosis measures. The Jarque-Bera evaluation further confirms these characteristics, indicating non-normality in the distribution of the exchange rate series.

To assess the stationarity of the time series, we employed multiple unit root tests. The KPSS stationarity test by Kwiatkowski et al. (1992) and the ZA unit root test by Zivot & Andrews (1992) were applied. The ZA unit root test results confirm that our return series are stationary, allowing for meaningful subsequent analysis. Additionally, the parameter stability test by Andrews (1993) provided evidence of parameter instability in both exchange rate series, indicating that the assumption of constant parameters does not hold. Moreover, the BDS test by Broock et al. (1996) was used to examine the independence and identically distributed (i.i.d.) nature of the residuals. The test results confirmed the failure of the i.i.d. assumption, suggesting that a linear model would be inappropriate. These findings collectively indicate that a time-varying analysis approach is more suitable for capturing dynamic interactions and dependencies in the exchange rate series. Those results indicated that the time-varying analysis approach is suitable.

3.2 Quantile cross spectral (coherency) approach

To begin, we let the LAK/USD and LAK/THB exchange rates be defined as two stationary processes denoted respectively as $X_t = \{x_t\}$ and $Y_t = \{y_t\}$, $t \in Z$. From Barunik & Kley (2019), we denote the dynamic dependency between the two stationary processes as:

$$R^{X,Y}(\omega, \tau_1, \tau_2) = \frac{F^{X,Y}(\omega, \tau_1, \tau_2)}{(F^{X,X}(\omega, \tau_1, \tau_2)F^{Y,Y}(\omega, \tau_1, \tau_2))^{\frac{1}{2}}} \quad (1)$$

where $-\pi \ll \omega \ll \pi$, $\tau \in [0,1]$, $F^{X,Y}$, $F^{X,X}$, and $F^{Y,Y}$ represent the quantile cross-spectral, and quantile cross-densities of processes $\{x_t\}$ and $\{y_t\}$, respectively. To capture the definition of the serial and cross-section dependence between $\{x_t\}$ and $\{y_t\}$, we use the kernel matrix of the quantile cross-covariance:

$$\Gamma_k(\tau_1, \tau_2) := (\gamma_k^{\tau_1, \tau_2}(\tau_1, \tau_2))_{XY} \quad (2)$$

where $\gamma_k^{\tau_1, \tau_2}(\tau_1, \tau_2) := \text{CoV}(I\{X_{t+k} \leq q_x(\tau_1)\}, I\{Y_t \leq q_y(\tau_2)\})$

for $K \in Z$ and distinctive function I . To provide further evidence on the nature of the cross-sectional dependency, we vary k to obtain information that relates to the serial dependency. This dependence produces the frequency domain metric:

$$F(\omega, \tau_1, \tau_2) := (2\pi)^{-1} \sum_{K=-\infty}^{\infty} \gamma_k^{\tau_1, \tau_2}(\tau_1, \tau_2) e^{-ik\omega} \quad (3)$$

We use smoothed quantile cross-periodograms to estimate the quantile coherency in each quantile level. Even though there are several quantiles, this study retains coherency for only three quantiles (0.5, 0.05, and 0.95) in addition to all their combinations, including the left, middle, and right tails of the distribution. Applying the above-mentioned quantiles enables us to examine the dependence on different sections of the distribution. On the other hand, we specifically adopt three frequencies: one week denoted as the short term, one month as the medium term, and one year as the long term.

Furthermore, $F(\omega, \tau_1, \tau_2)$ in Eq. (3) can be divided into two separate parts because it is a complex value. Thus, the real part is linked to the co-spectrum of the processes $(I\{X_{t+k} \leq X(\tau_1)\}_{t \in \mathbb{Z}})$ and $(I\{Y_t \leq q_Y(\tau_1)\}_{t \in \mathbb{Z}})$, while for the imaginary part, its purpose is to remove all sources of noise coherence that result from the instantaneous activity.

The quantile coherency method is superior to traditional and advanced econometric methods in numerous ways. This approach can capture the frequency domain aspect of the data (allowing for time-varying parameters) (Naeem et al., 2024). The advantages of the quantile spectral coherency approach are (i) it captures specific dependencies among the time series that remain hidden from other measures, (ii) it represents the independent variables causing a spurious relation, (iii) it is simple to interpret, and (iv) it does not require conditional moments, which is particularly important when we use the cross-spectrum to analyze financial time series (Baruník & Kley, 2019).

3.3 Time-frequency wavelet-based approach

We assume the time-series $\{X_n\}$ in which $n = 0 \dots N-1$, with δt time spacing, and a Morlet wavelet function $\psi_0(\eta)$ that depends on the non-dimensional “time” parameter (η). A simple form of the Morlet wavelet function is denoted as shown below:

$$\psi_0(\psi_0) = \pi^{\frac{1}{4}} e^{i\omega_0\eta_0 - \frac{1}{2}\eta^2}, \quad (4)$$

where ω_0 simplifies the non-dimensional frequency, which in our case is six, to fulfill the condition of admissibility following Farge (1992), and i is $\sqrt{-1}$.

The cross-wavelet transform of a discrete time series process $\{X_n\}$ of N observations with $\{X_n, n = 0, \dots, N-1\}$, scale s , and time step δt is written as shown below.

$$w_n^x = \frac{\delta_t}{\sqrt{s}} \sum_{n=0}^{N-A} x_{n^1} \psi^* \left((n - m) \frac{\delta_t}{s} \right) \quad (5)$$

with $m = 0, 1, \dots, N-1$

3.3.1 Wavelet power spectrum

We identify the local variance using the wavelet power spectrum denoted as $|W_n^x|^2$. We evaluate the significance of the wavelet power using the null hypothesis whereby the data-generating process is regarded as a stationary process having a definite background power spectrum of P_f . From the null hypothesis, the distribution of the local wavelet power spectrum is denoted as shown below:

$$D \left(\left(\frac{|W_n^x(s)|^2}{\sigma_x^2} < p \right) \right) = \frac{1}{2} P_f x_v^2, \quad (6)$$

where P_f represent the mean spectrum at the Fourier frequency f for the wavelet scale s , that is, $s \approx 1/f$. σ is the variance and χ^2 denotes the product of two stationary distributions. The likelihood devoted to a stationary process P_f is more than p , when v equals one for an actual wavelet and two for an intricate one. The processes in typical use are Monte-Carlo simulations (Mooney, 1997).

3.3.2 Cross-wavelet power (XWT)

Basing on the seminal paper of Hudgins et al (1993), the cross-wavelet power (XWT) which links time series, $\mathcal{X} = \{X_n\}$ and $y = \{y_n\}$ together as shown below:

$$W_n^{xy} = W_n^x W_n^{y*}, \quad (7)$$

where W_n^x and W_n^{y*} denotes wavelet transforms of time series $\mathcal{X}$ and y , correspondingly, while $|W_n^{xy}|$ represent the cross-wavelet power. When relying on the Fourier power spectra P_f^x and P_f^y , the WXT demonstrates the restricted covariance among the two-time series for each wavelet scale. ("Cross-spectral coherence and co-movement between WTI oil price and ...")

Following Torrence & Compo (1998), the distribution theoretically is

$$D\left(\left(\frac{|W_n^{xy}|}{\sigma_x \sigma_y} < p\right)\right) = \frac{Z_v(p)}{v} \sqrt{P_f^x P_f^y}, \quad (8)$$

where $Z_v(p)$ represent the confidence level of the likelihood p for a *pdf* signifying the square root of the product of the two series χ^2 distributions.

3.3.3 Wavelet coherency

Following Aguiar-Conraria et al. (2008), the wavelet coherency (WTC) is defined as:

$$R_n(S) = \frac{|s(s^{-1}W_n^{xy}(s))|}{S(s^{-1}|W_n^x|)^{\frac{1}{2}}S(s^{-1}|W_n^y|)^{\frac{1}{2}}} \quad (9)$$

where S reports the smoothing operator in both scale and time.

3.3.4 Phase difference

Building on the methodological framework pioneered by Aguiar-Conraria et al. (2008), the phase ϕ_x time series $\chi = \{\chi_n\}$ shows the point in the pseudo-cycle of the time series. The extension of status over $\chi = \{\chi_n\}$ and $y = \{y_n\}$ timer series, the phase difference $\phi_{x,y}$ represented by the mean and confidence interval of the phase difference, is of the form:

$$\phi_{x,y} = \tan^{-1}\left(\frac{\Im\{W_n^{xy}\}}{\Re\{W_n^{xy}\}}\right) \text{ and } \phi_{x,y} \in [-\pi, \pi], \quad (10)$$

where $\Re$ and $\Im$ denote the real and imaginary components of a complex-valued variable, following standard notation in spectral analysis. The two-time series in situations where the phase difference is 0 moves together at a specific frequency. Hence, we conclude the two series are in phase and χ leads y when $\phi_{x,y} \in [0, \frac{\pi}{2}]$, and y leads χ for $\phi_{x,y} \in [-\frac{\pi}{2}, 0]$. In terms of disparity, when the phase difference is $-\pi$ or π , we say that the two series are in anti-phase. Thus, χ lead y for $\phi_{x,y} \in [-\pi, -\frac{\pi}{2}]$, and y lead χ when $\phi_{x,y} \in [\frac{\pi}{2}, \pi]$.

3.3.5 Wavelet cohesion

Wavelet cohesion (WC) is established focusing on extreme nosy time series advanced by Rua, (2010) and Croux et al. (2001). Rua (2010) proposed a dependency approach $\rho_{\chi_n y_n}$ as a real number on $[-1, 1]$. The WC also captures the negative relationships and is denoted as:

$$\rho_{\chi_n y_n} = \frac{\Re(w_n^x w_n^y)}{\sqrt{|w_n^x|^2 |w_n^y|^2}}, \quad (11)$$

where $\Re$ represents the real part of the cross-wavelet spectrum of the $\chi = \{\chi_n\}$ and $y = \{y_n\}$ time series is estimated in the square root of two power spectra for the indicated time series in the denominator.

The time-frequency wavelet framework could analyze the time-frequency relationship as in the frequency domain framework; time information is lost. The wavelets tools, such as the wavelet power spectrum, cross-wavelet power (XWT), wavelet coherency (WTC), and wavelet phase difference, are used to analyze the impact of LAK/USD on the LAK/THB exchange rate and vice versa (Shahbaz et al., 2015; Afshan et al., 2018). There are several advantages of wavelet analysis over traditional techniques: (1) wavelet analysis could offer short-, medium-, and long-run frameworks; (2) wavelet analysis allows us detailed interaction between variables across different frequencies over time; Finally, (3) wavelet analysis could identify the lead-lag and cyclical vs. countercyclical status of the nexus.

4. Empirical Results

4.1 Descriptive Statistic

Table 2 provides a detailed overview of the descriptive statistics for the LAK/USD and LAK/THB exchange rates spanning from January 1990 to February 2024. The data source was from the Bank of the Lao PDR(2024)¹. Similar levels of volatility are displayed by both series, which have standard deviations of 0.0340 and 0.0320, respectively. Mild general swings during the study period are indicated by the mean monthly returns for LAK/USD and LAK/THB, which are 0.0080 and 0.0070, respectively. Both exchange rates display considerable deviations from what is typically expected. Whereas the LAK/THB exchange rate exhibits a skewness of 1.515 and a kurtosis of 29.850, the LAK/USD exchange rate exhibits a skewness of 2.902 and a kurtosis of 25.394. The observed values indicate significant fluctuations, as evidenced by the elevated Jarque-Bera test statistics, which lead to the rejection of the null hypothesis of normality at the 1% significance level for both series.

Several tests, including the Phillips-Perron (PP), KPSS, and Augmented Dickey-Fuller (ADF) tests, were used to confirm stationarity. The results of all tests show that the exchange rate series are stationary, enabling insightful further investigation. The detection of substantial autocorrelation and ARCH effects, as demonstrated by the Ljung-Box and ARCH-LM tests, underscores the necessity of employing time-varying models in the analysis.

¹ Bank of the Lao PRD: <https://www.bol.gov.la/index>

Table 2: The Summary of Variables' Statistics

Variables	LAK per USD	LAK per THB
Mean	0.0080	0.0070
Median	0.0000	0.0010
Max	0.2730	0.2800
Min	-0.1940	-0.2250
Std. Dev.	0.0340	0.0340
Skewness	2.902 *	1.515 *
Kurtosis	25.394 *	29.850 *
Jarque-Bera	9187.0 *	12533.4 *
ADF	-3.271456	-4.039 *
PP	-11.874 *	-13.344 *
KPSS	0.4319998	0.3185712
ZA	-4.333455	-5.02045
L-B	281.5 *	148.3 *
L-B ²	143.1 *	109.6 *
ARCH-LM (10)	77.1 *	66.3 *
Obs.	412	412

Note: * denotes significant at 1% level of significance.

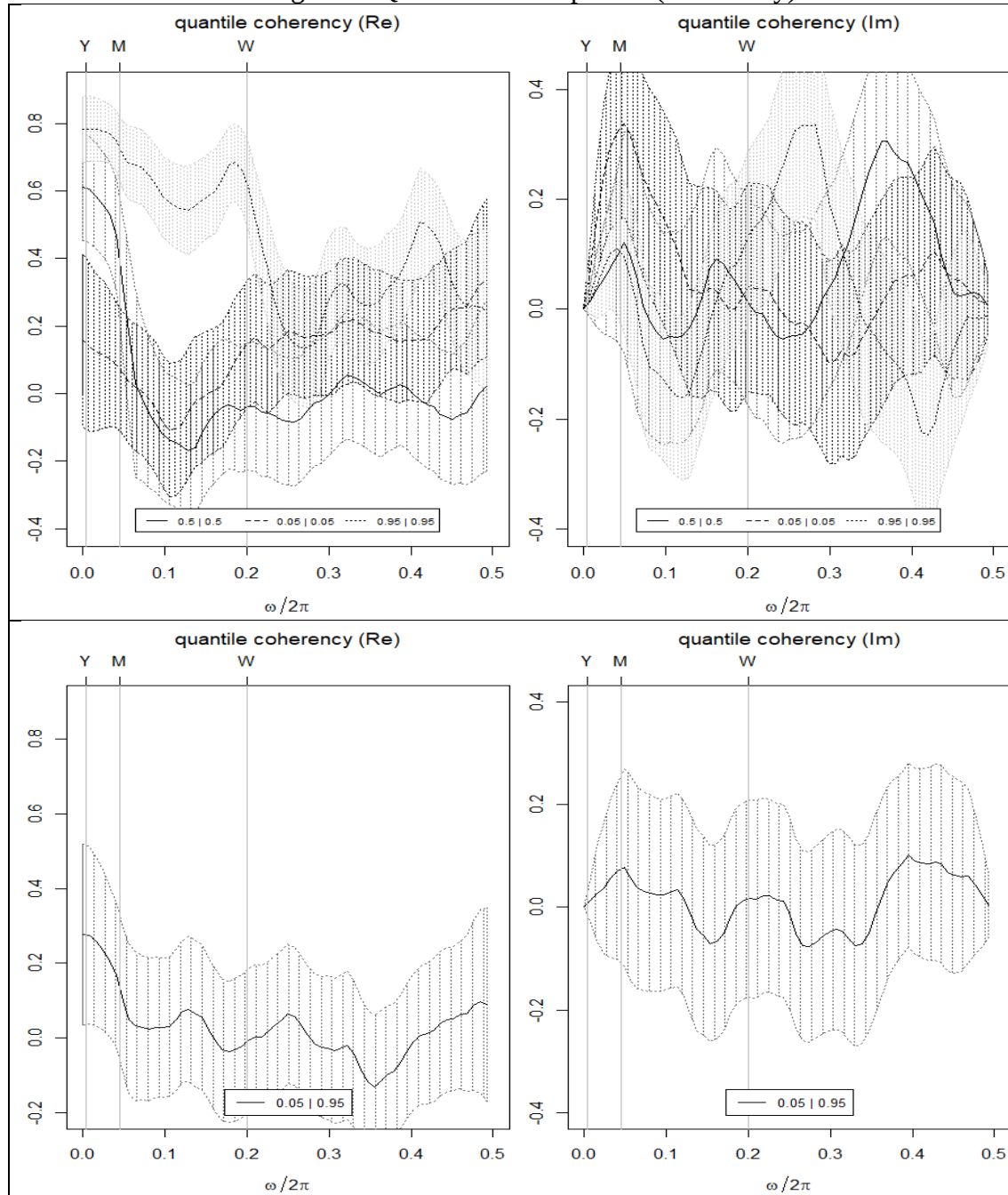
Sources: Author's Estimation in RStudio

4.2 Quantile coherency analysis

The quantile coherency figures demonstrate the correlation between the LAK/USD and LAK/THB exchange rates under varying market conditions. The left panel in each figure illustrates the real component of quantile coherency, whereas the right panel presents the imaginary component. The x-axis delineates a range of frequency bands, spanning from low frequency, indicative of long-term signals, to high frequency, which corresponds to short-term signals. The y-axis represents coherency levels, spanning from negative to positive values. Different quantile levels are illustrated by solid and dashed lines, demonstrating the variation of coherency across various market scenarios. The shaded regions represent the confidence intervals.

The initial figure illustrates that the real part exhibits a high positive coherency ranging from 0.6 to 0.8 at low frequencies for the 0.95 quantile, suggesting a significant level of synchronized movements during extreme positive market conditions. The 0.05 quantile indicates a positive coherency of 0.2 to 0.4 at low frequencies, implying a degree of synchronization under extreme negative conditions. The median quantile 0.5 exhibits coherency levels close to zero, suggesting minimal or absent co-movements in standard market scenarios. The analysis of the imaginary part reveals that the 0.95 quantile exhibits positive coherency up to 0.3 at medium frequencies, which implies a lead-lag relationship. Conversely, the 0.05 quantile presents a slightly negative coherency of -0.2 at higher frequencies, suggesting out-of-phase movements during downturns.

Figure 1: Quantile Cross Spectral (Coherency)



Notes: 1. The quantile coherency graphs show the relationship between the LAK/USD and LAK/THB exchange rates across different quantiles (0.05, 0.5, 0.95) for both the real (Re) and imaginary (Im) parts.

2. The left panel in each figure represents the real part of the coherency (Re), while the right panel represents the imaginary part (Im).

3. The x-axis shows the frequency range from long-term (low frequency) to short-term (high frequency), with the Y, M, and W markers denoting yearly, monthly, and weekly periods, respectively.

4. The y-axis measures the coherency level, where positive values indicate in-phase movement, and negative values indicate out-of-phase movement.

5. The shaded areas represent the confidence intervals for the coherency estimates, providing an indication of the reliability of the observed relationships.

Sources: Author's Estimation using R Studio

The second illustration highlights a decrease in positive coherency for the 0.95 quantile from 0.2 to 0.3 at long-term frequencies, suggesting diminished synchronized movements during extreme positive conditions. The 0.05 quantile continues to show positive values, albeit at reduced levels of 0.1 to 0.2, indicating diminished co-movements during extreme negative scenarios. The imaginary component exhibits negligible variation, as evidenced by the 0.95 quantile being slightly positive at approximately 0.1 and the 0.05 quantile nearing zero, suggesting minimal phase discrepancies.

To summarize, over the course of a year, the findings indicate a significant co-movement among the exchange rates, with coherency values frequently surpassing 0.6 at elevated quantiles, e.g., 0.95. The strong synchronization indicates that macroeconomic fundamentals and external shocks, including global crises, significantly influence the alignment of the two currencies over extended periods. At lower quantiles, e.g., 0.05, the co-movement remains observable but shows a tendency to diminish, indicating the influence of unfavorable economic conditions. The analysis indicates that the LAK/USD exchange rate consistently precedes the LAK/THB over these extended time frames, underscoring the significant role of the U.S. dollar in shaping regional currency movements.

At the monthly scale, the co-movement exhibits increased variability, with coherency values fluctuating between 0.3 and 0.6 across different quantiles. In scenarios characterized by extreme positive conditions (quantile 0.95), a notable degree of moderate co-movement remains evident. This indicates that intermediate factors, including seasonal trade cycles, changes in monetary policies, or moderate external shocks, play a significant role in shaping the relationship. At lower quantiles (0.05), co-movement significantly diminishes, highlighting the critical role of external shocks in affecting currency alignment. The lead-lag relationships identified at this scale exhibit variability, as the LAK/THB sometimes react to regional dynamics instead of adhering closely to the U.S. dollar. This variability underscores the necessity of observing medium-term economic developments that may impact long-term trends.

At the weekly scale, short-term interactions exhibit weaker and more sporadic co-movement, with coherency values varying between 0.1 and 0.3 based on the quantile. In favorable market conditions at the 0.95 quantile, a certain level of synchronization can be detected; however, it is not uniform and is influenced by speculative trading or localized market noise. In contrast, during stressed conditions at the 0.05 quantile, the co-movement significantly decreases, suggesting that short-term influences like speculative behavior and external volatility prevail at this frequency. The lead-lag dynamics at this level exhibit increased variability, with neither currency consistently impacting the other, indicative of short-term market adjustments and external influences.

The quantile coherency results highlight the significance of market conditions in influencing these relationships. In extreme positive market scenarios at the 0.95 quantile, a significant co-movement is noted, especially over longer time scales, suggesting a pronounced alignment during favorable economic conditions. In contrast, during times of market stress at the 0.05 quantile, the co-movement notably diminishes, highlighting the impact of structural economic disparities and external shocks on disrupting currency synchronization.

4.3 Wavelet-based analysis

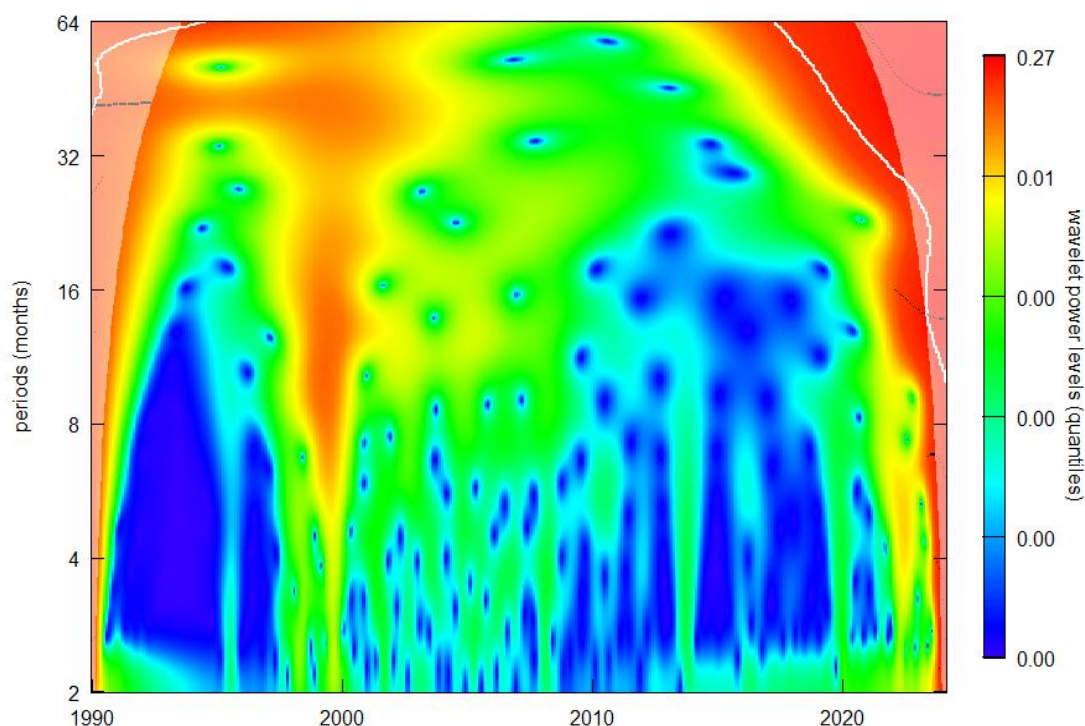
The wavelet-based analyses, which are shown in Figures 2 through 5, look at how the LAK/USD and LAK/THB exchange rates interacted between the data timeframes. The x-axis in these images represents time, while the y-axis displays periods that range from short-term (2 months) to long-term (128 months). The color gradient, transitioning

from blue to red, signifies the intensity of interactions, coherence, or phase differences, contingent upon the analysis conducted.

4.3.1 CWT power spectra

The evidence presented in Figure 2 highlights clear intervals of notable volatility in the LAK/USD exchange rate. Between the late 1990s and early 2000s, particularly from 1997 to 2003, notable cyclical activity was present in long-term cycles, exhibiting significant power within the 16 to 64-month frequency bands. The power levels observed during this period peak at 0.27 (red regions), signifying significant volatility in the LAK/USD exchange rate.

Figure 2: CWT Power Spectrum of LAK/USD



Note: 1. The left panel shows the Continuous Wavelet Transform (CWT) power spectrum for the LAK/USD exchange rate, and the right panel shows the CWT power spectrum for the LAK/THB exchange rate.

2. The y-axis represents the period in months, where larger values (e.g., 32, 64) correspond to long-term cycles (years), and smaller values (e.g., 2, 4) represent short-term cycles (months).

3. The color scale indicates wavelet power levels: Blue: Represents low power, indicating weaker cyclical activity or less pronounced periodic behavior at the corresponding frequency. Red: Represents high power, indicating stronger cyclical activity, meaning the exchange rates exhibit more intense or consistent fluctuations at the given frequency and period.

4. High wavelet power (red areas) suggests periods when the exchange rates experience strong, regular movements over the indicated cycle (e.g., yearly, monthly).

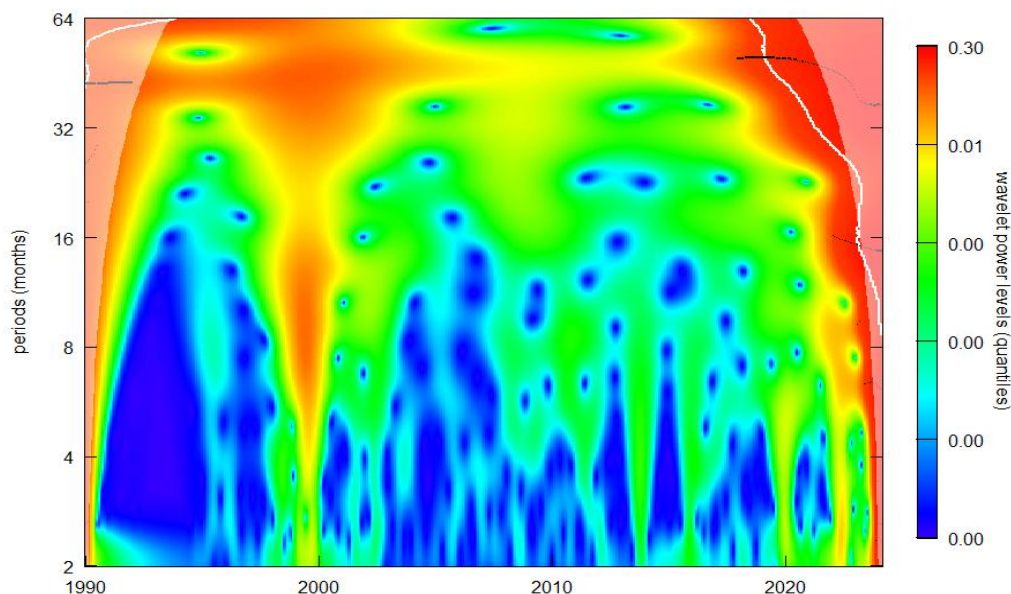
5. The white contour lines highlight areas of statistically significant power at the 5% level.

Sources: Author's Estimation using RStudio

This timeframe corresponds with the Asian Financial Crisis, which resulted in significant economic disturbances across Southeast Asia. A subsequent phase of increased power is observed from 2020 to 2024, with power levels rising to 0.27, especially within the 16- to 32-month intervals, indicative of the notable variations in the

exchange rate resulting from the COVID-19 pandemic. This period demonstrates pronounced cyclical patterns, reflecting the global and regional economic uncertainties that arose during the pandemic. Conversely, diminished power levels (blue regions) are noted in the early 1990s and the mid-2010s, especially within the 2- to 8-month cycles, indicating a period of relative stability and decreased volatility in the exchange rate during these intervals.

Figure 3: CWT Power Spectrum of LAK/THB



Note: 1. The left panel shows the Continuous Wavelet Transform (CWT) power spectrum for the LAK/USD exchange rate, and the right panel shows the CWT power spectrum for the LAK/THB exchange rate.

2. The y-axis represents the period in months, where larger values (e.g., 32, 64) correspond to long-term cycles (years), and smaller values (e.g., 2, 4) represent short-term cycles (months).

3. The color scale indicates wavelet power levels: Blue: Represents low power, indicating weaker cyclical activity or less pronounced periodic behavior at the corresponding frequency. Red: Represents high power, indicating stronger cyclical activity, meaning the exchange rates exhibit more intense or consistent fluctuations at the given frequency and period.

4. High wavelet power (red areas) suggests periods when the exchange rates experience strong, regular movements over the indicated cycle (e.g., yearly, monthly).

5. The white contour lines highlight areas of statistically significant power at the 5% level.

Sources: Author's Estimation using RStudio

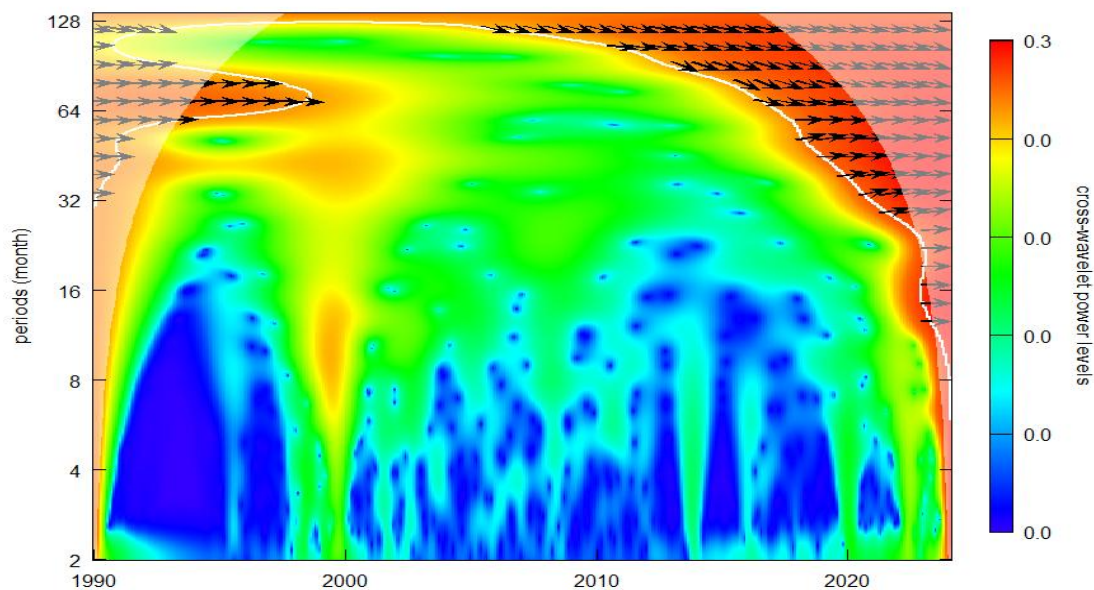
In a comparable manner, Figure 3 illustrates that the LAK/THB exchange rate exhibited significant strength during the corresponding time frames. From 1997 to 2003, there is a notable increase in power within the 16- to 64-month frequency bands, with power levels attaining 0.30, indicating considerable fluctuations attributed to the Asian Financial Crisis. Furthermore, from 2020 to 2024, the LAK/THB exhibits significant cyclical fluctuations within the 16- to 32-month intervals, with power levels reaching approximately 0.30, which aligns with the COVID-19 pandemic and its subsequent economic effects. In the early 1990s and parts of the 2010s, the presence of lower power in the 2- to 8-month bands suggests a pattern of more stable exchange rate movements, characterized by a reduction in disruptions.

4.3.2 Cross-Wavelet Power (XWT)

The cross-wavelet power spectrum in Figure 4 reveals several key periods of significant co-movement between the LAK/USD and LAK/THB exchange rates. From

the late 1990s to the early 2000s, there is a distinct region of high power in the 32- to 64-month cycles, which aligns with the Asian Financial Crisis. During this period, the phase arrows indicate that LAK/USD consistently led LAK/THB, suggesting that fluctuations in the LAK/USD exchange rate influenced the movements of the LAK/THB. As we move into the early 2000s, moderate power in the 16- to 32-month cycles shows continued co-movement, with LAK/USD still leading, although the influence appears less intense compared to the previous period.

Figure 3: Cross-Wavelet Power Spectrum between LAK/USD and LAK/THB
Cross-Wavelet Power Spectrum between LAK/USD and LAK/THB



Note: 1. The cross-wavelet power spectrum shows the co-movement between two time series (LAK/USD and LAK/THB) across time and frequency domains. The color scale is the same with fig. 2 and fig. 3.

2. Phase arrows indicate the lead-lag relationship:

- Right: The series are in phase.
- Left: The series are out of phase.
- Up-right: LAK/USD leads LAK/THB.
- Down-left: LAK/THB leads LAK/USD.

The cone of influence (light-shaded area) marks regions affected by edge effects, where results should be interpreted cautiously.

Source: Author's Estimation using RStudio.

During the mid-2000s, there is a noticeable weakening in co-movement, evidenced by reduced power levels in the 8- to 16-month cycles. Nonetheless, LAK/USD remains at the forefront, though its influence on the LAK/THB exchange rate is diminished. The duration of diminished engagement aligns with a phase of comparative global economic steadiness preceding the 2008 monetary crisis. During the period from 2008 to 2012, coinciding with the Global Financial Crisis, there is a notable resurgence of power, especially evident in the 16- to 64-month cycles. The phase arrows during this period indicate that LAK/USD was pivotal in guiding the LAK/THB, demonstrating the impact of USD-related factors on both currencies amid increased global volatility.

As we progress into the mid-2010s, there is a noticeable decline in power levels within the 8- to 16-month cycles, suggesting a diminished co-movement among the currencies. The decrease in influence indicates a more stable recovery phase following the crisis. Beginning in 2015 and extending to 2019, there is a notable increase in power levels in 2020 to 2024, especially within the 32- to 128-month cycles, which aligns with

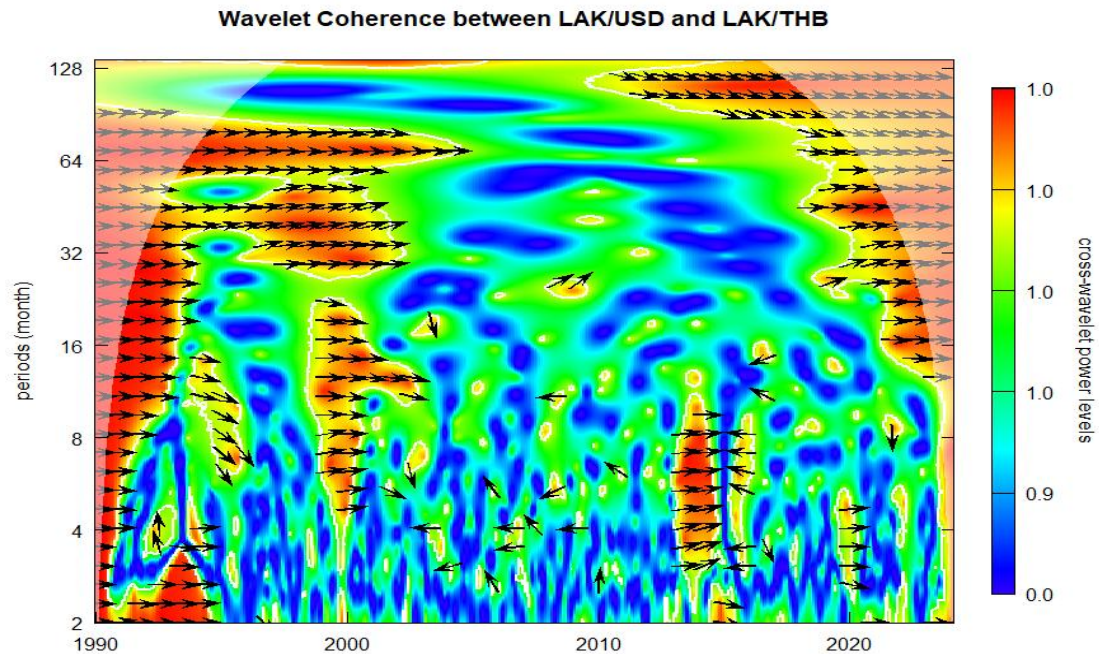
the global disruptions resulting from the Covid-19 pandemic. Throughout this period, LAK/USD has once more outperformed LAK/THB, with the pronounced co-movement indicating the substantial influence of the pandemic on both regional and global exchange rate dynamics.

4.3.3 Wavelet coherency (WTC)

The connection between these two exchange rates has shown fluctuating levels of co-movement throughout various economic cycles, indicating the influence of both regional and global economic occurrences. Figure 5 illustrates the wavelet coherence between these two exchange rates, offering a comprehensive examination of the evolution of their correlation over time and across various time frequencies. The figure illustrates significant intervals during which the two currencies exhibited parallel movements, alongside instances of divergence, providing a deeper understanding of the factors influencing their relationship. A notable period of high coherence is observed from the late 1990s to the early 2000s, especially between 1997 and 2002, within the 32- to 64-month intervals. This period aligns with the Asian Financial Crisis, characterized by significant economic turmoil throughout Southeast Asia. The arrows in this region direct upward and to the right, indicating a clear trend where LAK/USD is leading LAK/THB. The data indicates that variations in the LAK/USD exchange rate were influencing shifts in the LAK/THB, highlighting the significant impact of USD-related dynamics during this crisis. Between the early 2000s, specifically from 2003 to 2006, a distinct quiver of arrows can be identified within the 16- to 32-month intervals. The direction of these arrows indicates an upward and rightward trend, reinforcing the established pattern of LAK/USD preceding LAK/THB. This period illustrates the recovery following the crisis, during which the USD continued to play a pivotal role in shaping the dynamics of regional exchange rates. The mid-2000s, particularly from 2006 to 2010, exhibit a notable concentration of phase arrows within the 8- to 16-month intervals. During this period, the arrows consistently point in the same direction, suggesting that LAK/USD has remained dominant over LAK/THB. This timeframe aligns with the worldwide recovery after the Global Financial Crisis, during which the LAK/USD significantly impacted regional currency fluctuations. A significant interval of elevated coherence is observed from 2015 to 2024, particularly within the 32- to 128-month spans. This period corresponds with the COVID-19 pandemic, a worldwide occurrence that resulted in significant financial and economic disruption. The arrows in this region, consistently directed upward and to the right, highlight the ongoing impact of LAK/USD on LAK/THB throughout this extended phase of uncertainty.

Furthermore, shorter-term cycles, specifically the 4- to 8-month intervals observed in the late 1990s and early 2000s, demonstrate significant co-movement. The arrows indicate that LAK/USD consistently led LAK/THB, even within these shorter, more frequent cycles. The findings indicate that the LAK/USD maintained a consistently influential role during significant global economic events, influencing the fluctuations of the LAK/THB. Conversely, the early 1990s and certain segments of the 2010s exhibit a reduced number of arrows and diminished coherence, suggesting a lack of strong correlations and lower synchronization between the two exchange rates.

Figure 4: Wavelet Coherence between the LAK/USD and LAK/THB



Note: 1. Wavelet coherence measures the degree of correlation between two time series, in this case, LAK/USD and LAK/THB, over time and across different frequencies. This helps identify when and how closely the two exchange rates move together.

2. While cross-wavelet power (Figure 4) captures the strength of co-movement, wavelet coherence emphasizes the consistency of this correlation, regardless of the magnitude of fluctuations.

3. Higher coherence values in red regions (close to 1) indicate strong synchronization between LAK/USD and LAK/THB exchange rates across certain periods. Lower coherence in blue regions signifies weaker correlation.

The arrows in this figure continue to indicate the lead-lag relationship (same as in Figure 4), but the focus here is on the stability and consistency of co-movement, rather than the intensity of power.

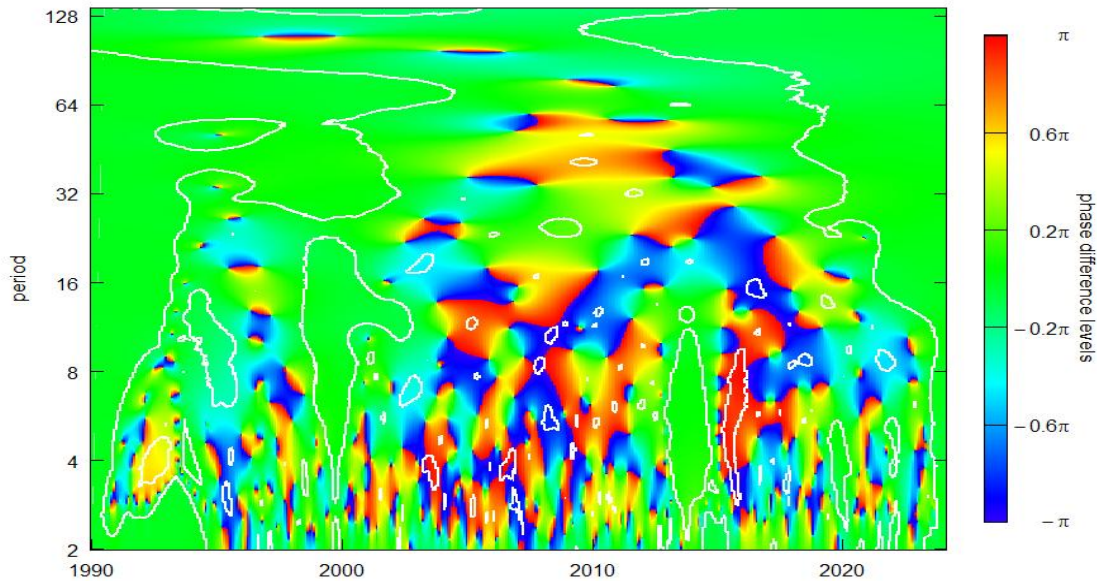
Source: Author's Estimation using RStudio

4.4 WC based on the Rua (2010)

Figure 6 illustrates the evolving lead-lag relationships between the LAK/USD and LAK/THB exchange rates throughout the observed period. During the late 1990s to early 2000s, a distinct pattern emerges with positive phase differences, especially evident in the longer cycles, where LAK/USD precedes LAK/THB. This refers to the timeframe after the Asian Financial Crisis, during which fluctuations in LAK/USD notably impacted the LAK/THB exchange rate. In the mid-2000s, although LAK/USD maintains its dominance over longer cycles, shorter cycles start to exhibit blue regions, signifying periods where LAK/THB temporarily outperforms LAK/USD. This reversal occurs infrequently and lacks durability.

From 2010 to 2019, there was a clear decline in significant lead-lag relationships, evidenced by the emergence of numerous white areas, which indicate weaker interactions and a more stable economic environment. Between 2020 and 2024, the data illustrates a notable increase in positive phase differences in longer cycles, with LAK/USD once more taking precedence over LAK/THB, especially throughout the Covid-19 pandemic. This suggests that variations in the LAK/USD exchange rate had a significant impact on the LAK/THB during this challenging time. Intermittent blue areas emerge in shorter cycles, indicating brief periods where LAK/THB takes the lead; however, these occurrences are not as significant.

Figure 5: Phase Difference Over Time.



Note:

1. Phase difference shows the lead-lag relationship between two time series (LAK/USD and LAK/THB). It indicates which exchange rate leads or lags the other over time and across different frequencies.
2. The color scale represents phase difference values:
 - Red and yellow areas: Positive phase difference, meaning LAK/USD leads LAK/THB.
 - Blue areas: Negative phase difference, meaning LAK/THB leads LAK/USD.
 - Green areas: Represent synchronization, where both exchange rates move together without a clear leader.
 - White areas: Indicate no significant phase difference, reflecting weak or irregular interaction between the exchange rates.

The white contours outline regions of significant phase differences, indicating statistically meaningful lead-lag relationships.

Source: Author's Estimation using RStudio

5. Conclusion and Policy Recommendation

Recognizing the importance of understanding the dynamic interactions between exchange rates at different time frequency levels, this study employs wavelet-based tools, including wavelet coherence and quantile cross-spectral analysis, to investigate the co-movement of the LAK/USD and LAK/THB exchange rates over the period from January 1990 to February 2024. These methods provide a nuanced understanding of frequency-specific relationships and their evolution over time, particularly during periods of economic turbulence.

The analysis indicates that the relationship between the LAK/USD and LAK/THB exchange rates exhibits variability across time periods and scales. Wavelet coherence analysis reveals notable synchronization during times of economic turbulence, particularly between 1997 and 2003 and 2020 and 2024, underscoring the significant influence of the U.S. dollar on regional currency dynamics (Nikkinen et al., 2011). At lower frequencies (long-term cycles), the LAK/USD exchange rate consistently leads the LAK/THB, demonstrating the U.S. Dollar's pivotal role. However, in higher frequencies

(short-term cycles), instances were observed where the LAK/THB exhibited leadership, reflecting localized market adjustments and regional dynamics (Yang et al., 2016).

The quantile coherency analysis supports these findings, showing pronounced co-movement during extreme positive market conditions (0.95 quantile) with coherency values frequently exceeding 0.6. During economic downturns (0.05 quantile), weaker but still consistent correlations were observed, with values ranging between 0.2 and 0.4, highlighting the persistent influence of external shocks on currency alignment (Dias & Embrechts, 2010; Kumar et al., 2017). Elevated frequencies (short-term cycles) demonstrated more irregular patterns of co-movement, influenced by speculative trading, market noise, and localized economic events (Orlov, 2009; Boubaker & Boutahar, 2011).

These findings emphasize the hierarchical structure of exchange rate interactions and highlight how the time horizon influences currency relationships. At lower frequencies, macroeconomic fundamentals and structural factors dominate, while short-term cycles are shaped by immediate market reactions and speculative behavior (Aguar-Conraria et al., 2008).

To stabilize the Lao Kip (LAK) and safeguard regional trade with Thailand and neighboring economies, evidence-based strategies must account for volatility across short, medium, and long-term horizons, as well as external USD-linked shocks. Short-term dynamics (weekly/monthly cycles) are marked by weak co-movement (quantile coherency: 0.1-0.3) between LAK/USD and LAK/THB, driven by speculative trading, localized noise, and oil price fluctuations. For instance, Laos's structural vulnerability to global oil shocks exacerbates LAK depreciation; as seen in 2022, surging prices for fuel imports offset the country's export growth and worsened external imbalances, contributing to the kip falling by 32% against the Thai baht and 43% against the US dollar by early 2023 (World Bank, 2023). Wavelet analysis confirms heightened volatility in 4–8-month cycles during crises like the 1997-2002 Asian Financial Crisis and where LAK/USD consistently led LAK/THB (upward/rightward phase arrows). These patterns mirror studies on high-frequency forex markets, where speculative activity amplifies intraweek fluctuations (Menkhoff et al., 2012). To mitigate such risks, BoL should deploy tactical tools like short-dated options (Allayannis et al., 2001) and THB-denominated futures during speculative surges (e.g., 2015-2024 cycles), offsetting arbitrage-driven distortions (Menkhoff et al., 2012).

Medium-term cycles (8-16 months) exhibit moderate co-movement (quantile: 0.3-0.6), reflecting cyclical trade dependencies and U.S. interest rate spillovers. Global monetary tightening, such as the Federal Reserve rate hikes in 2022-2023, tightens regional financial conditions and exacerbates exchange rate depreciation; this indirectly pressures the LAK and substantially increases the domestic currency burden of Laos's THB-denominated external debt (IMF, 2023). Post-2008 wavelet coherence underscores LAK/USD leadership during liquidity shocks, reaffirming Thailand's role as Laos's dominant trade partner (World Bank, 2023). For these risks, portfolio diversification into currency baskets (e.g., LAK, THB, USD) aligns with seasonal trade flows (Azar, 2010), such as increasing THB holdings before Thailand's harvest season (Kawai & Pontines, 2016). This approach, grounded in modern portfolio theory (Markowitz, 1952), reduces exposure to cyclical liquidity strains.

Long-term structural shifts (32-128-month cycles) reveal stark contrasts: strong co-movement (0.6-0.8 at the 0.95 quantile) during bullish phases and weaker linkages (0.2-0.4 at the 0.05 quantile) in bearish periods. Persistent U.S. inflation (e.g., post-COVID 2021–2023) amplifies these trends, as Fed policies strengthen the USD, forcing Thailand to raise rates to defend the THB, a “double shock” that strains Laos's dollarized debt (public external debt: 65% of GDP in 2024). Wavelet coherence during prolonged crises (e.g., 1997-1999, 2020-2024) highlights the LAK's structural dependency on

USD/THB dynamics, consistent with the USD's "safe haven" role (Brunnermeier et al., 2008). Policymakers should prioritize diversifying forex reserves into THB (World Bank, 2023) while maintaining USD/THB liquidity buffers during downturns (Calvo & Reinhart, 2002). During stability (0.95 quantile), investors can leverage high co-movement for carry trades (Brunnermeier et al., 2008), whereas bearish phases demand crisis-ready reserves.

The Lao Kip's chronic depreciation has fueled widespread dollarization, with households and businesses hoarding THB and USD to hedge against inflation and currency risk. This weakens monetary policy transmission, exacerbates LAK volatility, and entrenches a vicious cycle of currency substitution. To reverse this trend, the Bank of Laos must adopt a multi-pronged strategy: First, interest rate reforms such as raising LAK deposit rates above inflation (e.g., 26.2% in 2024) to incentivize savings in local currency. For example, introducing inflation-indexed LAK bonds (e.g., 12-month bonds yielding 28%) could attract domestic capital while reducing reliance on foreign currencies. Second, stricter FX regulations like limiting THB/USD transactions for domestic purchases (e.g., mandating LAK for all in-country contracts under USD 10,000) while exempting critical imports like fuel. Third, digital financial inclusion launches a central bank digital currency (CBDC) or mobile wallet systems (e.g., "LAK-Pay") to improve access to LAK liquidity in rural areas, where THB dominates 60% of cross-border transactions. These measures should be paired with public trust campaigns, such as guaranteed LAK convertibility for essential goods and transparent FX intervention policies. Critically, Thailand's cooperation is vital: harmonizing cross-border trade settlement systems (e.g., a Lao-Thai QR payment corridor) could reduce transactional THB demand while preserving trade flows. Without such reforms, dollarization will deepen, rendering the LAK a mere unit of account rather than a store of value.

The observed co-movement and lead-lag relationships during periods of market duress highlight the significance of coordinated regional monetary policies, such as Laos and Thailand, to stabilize these exchange rates. The considerable impact of the U.S. dollar on both currencies underscores the importance of closely monitoring global financial developments to mitigate risks arising from external disruptions (Aloui & Hkiri, 2014).

Future research may enhance this framework by integrating further macroeconomic variables, including trade balances, capital flows, and inflation rates, to analyze their influence on exchange rate dynamics. Furthermore, examining the interconnections between the LAK and a wider array of regional currencies, including the Chinese Yuan (CNY) and Vietnamese Dong (VND), may provide deeper insights into the impact of regional economic integration on currency relationships. High-frequency datasets, such as intraday data, can offer detailed insights into speculative trading behaviors and short-term market fluctuations, thus enhancing our comprehension of exchange rate dynamics in Southeast Asia.

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