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# Unveiling Time-Frequency Quantile Connectedness in the Asian Forex Market

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**Abstract:** This study examines the quantile connectedness between foreign exchange returns of eight major currencies in the Asian foreign exchange market during two major crises: the Global Financial Crisis of 2008 and the COVID-19 Pandemic Crisis. This paper uses the Quantile Vector Auto-Regression method (QVAR) by exploring the time and frequency connectedness among the Asian foreign exchange market under extreme events. Based on the daily exchange rate data of eight major Asian currencies from 2005 to 2024, the results show that the connectedness measures in the left and right tails are much higher than those in the median. This indicates that return connectedness strengthens with shock for both positive and negative shocks, showing that shocks to returns propagate more intensely during extreme events relative to tranquil periods. The paper concludes that going beyond mean-based connectedness measurements is necessary to comprehend return connection under extreme negative and extreme positive shocks. These results provide valuable insights to investors and policymakers regarding risk mitigation under global uncertainties.

**Keywords:** Quantile Connectedness; QVAR; Crisis; Shocks; Asian Currencies

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## 1. Introduction

Numerous occurrences, such as the Global Financial Crisis (GFC) of 2008 and the COVID-19 crisis, have demonstrated the futility of looking at a market in isolation. Events, including falling stock prices, stagnant global economic activity, and increased market volatility, among others, have become commonplace worldwide [1]. Assessing the financial impact of the crisis becomes expedient from a policy standpoint as the crisis unfolds with extreme volatility, especially in the highly integrated financial markets. The foreign exchange market, one of the major players in the financial market, faces unstable capital flows during crises, and they are more vulnerable to changes in the global financial markets. So, there will be a 'Contagion Effect' in these markets.

Following the global financial globalization, foreign exchange markets, one of the major financial markets, became extremely intertwined. Due to growing trade integration, capital flow liberalization, and strengthening financial ties between the economies, the foreign exchange markets, particularly in Asia, have grown extremely intertwined since the wave of financial globalization. Increased intraregional trade, increased financial openness, and the growing influence of large regional economies like China, Japan, and India have all contributed to the significant growth of these interdependencies in the Asian context. Because of this, changes in one Asian economy's exchange

rate can have a significant impact on others, making it more difficult to implement monetary policy and increasing susceptibility to outside shocks. Designing efficient exchange rate regimes, coordinating regional policies, and strengthening resilience against global financial instability all depend on an understanding of such spillovers.

As a result, shifts in the value of one Asian economy's currency can quickly impact other economies, causing significant ripple effects. The exchange rates are the primary means of transferring shocks from one economy to another; it is crucial to analyze the degree of their connectivity. The Asian foreign exchange market plays a crucial role in directing capital into development projects in many Asian countries. It performs an arbitrage function between markets in Asia, the Middle East, and Europe [2,3]. In the Asian foreign exchange market, the most typical regime is managed float, which is pegged. The shift in the exchange rate regime also plays a vital role in determining the spillovers. This information demonstrates that, before the 1997 financial crisis, nations frequently opted for fixed or floating exchange rates, sometimes known as corner or bipolar [4] or "hollow middle" solutions [5]. Interdependencies across foreign exchange markets are crucial for international trade, risk management, portfolio diversification, and the policies of monetary authorities [6].

This paper considers eight major currencies in the Asian foreign exchange market to analyze the degree of connectedness between these currencies. Those currencies are Yen, Yuan, Won, Rupees, Ringgit, Baht, Singapore Dollars, and Hong Kong Dollars. These currency pairs are more likely to be vulnerable to greater risks and uncertainties than less-traded currencies due to the high volume of foreign exchange. To reduce the effects of shocks to the foreign exchange transmission channel, policymakers must develop a thorough understanding of the spillovers in this market.

The theoretical underpinnings of this study are derived from the literature on financial contagion, which [7] categorizes into two groups: crisis contingent theories and non-crisis contingent theories. The crisis-contingent theories propose that pure contagion happens because of several equilibria and self-fulfilling crises by [8,9]. Crisis-contingent theories contend that the spread of contagion differs between times of stability and crises. According to these views, there is "pure contagion" during crises, which is characterized by excessive volatility and market co-movements that cannot be fully explained by the fundamentals. The basic idea behind crisis-contingent theories is that unexpected and disproportionate spillovers across markets, particularly in foreign exchange markets, occur when financial instability increases the intensity of transmission channels. On the other hand, the "non-crisis-contingent" theories are used to describe fundamental contagion, which holds that market transmission mechanisms result from the interdependence of international trade [10]. These non-crisis theories hold that financial contagion has the same extent and impact during times of stability as it does during times of crisis. According to this view, contagion is a reflection of interdependence, and thus, the extent and pattern of transmission remain broadly consistent during both tranquil and turbulent periods. Contrarily, crisis-contingent theories propose that pure contagion happens because of several equilibria and self-fulfilling crises by [8,9]. Crisis-contingent theories contend that the spread of contagion differs between times of stability and crises. According to these theories, spillovers become exacerbated and asymmetric in extreme situations in financial markets.

This study extends the mean-based vector autoregression (VAR) approach of [11] to the quantile-based measures to capture this asymmetry in the context of the Asian foreign exchange market. The

traditional VAR model does not capture the spillover between the markets by analyzing their asymmetric behaviour during the extreme events. This study mainly focuses on static and dynamic connectedness between the currencies across the upper and lower quantiles, which is more suitable for analyzing the impacts of global uncertainties more robustly. Since it can determine whether exchange rate spillovers occur in the tails of the distribution, this method is especially well-suited to testing the validity of crisis-contingent theories. Here, VAR models are fitted at upper and lower quantiles to capture the effects of shocks during extreme events. One of the major advantages of the quantile-based connectivity is, it can explain the magnitude of the tail risks; the impact of positive and negative shocks in a market. The study reveals the tail dependency structure of the network of return spillovers in the Asian foreign exchange rate markets by using a quantile-based method of connectivity, whereby aids in explaining the spread of tail risk in the Asian exchange rate markets, a significant topic that has hitherto been overlooked in earlier research [12,13,14,15,16,17,18].

This study is significant and timely because the degree of economic interdependence between the countries has increased due to the integration of global markets, and uncertainties have also increased. All these methodologies fail to address the question of how does foreign exchange market behaves under extreme events in the time and frequency domain. The time-frequency domain analysis reveals how spillovers change before, during, and after a shock. The frequency domain, on the other hand, reveals the horizon and duration of these spillovers, differentiating between long-term and short-term responses of a market. Because markets may react quickly in the short term but adjust differently over longer time horizons, especially during crises, this dual approach is especially crucial during crises. Ignoring either area puts policymakers at risk of overlooking important facets of market behavior that are essential to putting timely and successful interventions into place. This will be beneficial for the investors and policymakers to formulate a more resilient strategy. However, as interconnectedness has grown, it has become more challenging for an economy to pursue an action inconsistent with global economic realities. Investors, risk managers, and policymakers are therefore concerned about the independence of the currency rates.

This study aims to bridge these research gaps by utilizing Quantile Vector Autoregressive (QVAR) methodology in the time and frequency domain to explore the non-linear relationships and short- and long-term dynamics in the Asian foreign exchange market. This study's primary objective is to analyse the interdependencies and spillover effects on the major Asian currencies by exploring the short- and long-term dynamics in these markets, aiming to delve deeper into the interconnections between these major Asian currencies. The study also proposes adaptive risk management strategies based on the observed dynamics, thereby contributing to the broader discourse on risk management in the Asian foreign exchange market. The study includes a novel quantile and frequency connectedness approach, along with a comprehensive examination of the impact of various crises on these indices, including the GFC and the COVID-19 pandemic. This analysis is anticipated to be crucial for comprehending market dynamics, risk management, investment strategies, and policy development in light of global financial trends and the interdependence of emerging markets. The decision to focus on the Asian foreign exchange market, encompassing some of the foremost emerging economies, is underpinned by a series of critical considerations. Examining the Asian foreign exchange market gives a thorough rundown of how emerging markets respond to international crises; together, these nations wield significant influence on the world economy. This work contributes to the existing body of literature by providing a comprehensive examination of the

frequency and temporal domains, thereby capturing the intricate dynamics of market interactions across a range of time and quantiles. The results provide practical guidance for financial professionals and policymakers, highlighting the importance of flexible risk management techniques and the development of informed policies to address the impending financial turmoil.

Following this introductory section, the structure of the rest of the paper is as follows. Section 2 presents a review of the existing literature; Section 3 explains the data and methodology used in our analysis. Section 4 discusses the empirical results. Section 5 concludes the study.

## **2. Literature Review**

This section presents a review of the literature on existing studies related to spillovers and connectedness in the global foreign exchange market and regional foreign exchange markets. Numerous studies have examined the connectedness and spillovers between various markets in terms of returns and volatility. However, fewer empirical investigations have reported on the spillovers and connectedness in the Asian foreign exchange market during the two major crises.

An increasing body of studies has focused on foreign exchange volatility and returns spillovers using short-term and long-term statistical methodologies. These studies include [19,20,21,6,11]. For example, [19] in his paper showed the existence of intra-day volatility spillovers on the forex market (“meteor shower hypothesis” 1) rather than being country-specific (“heat wave hypothesis” 2). Although volatility spillovers inside an area are significant economically, they find that informational links are statistically significant at both the own-region and inter-region levels.

The preceding literature on exchange rate volatility spillover in regional markets is also vast. There is a substantial corpus of research on identifying and explaining spillover effects across various geographic markets. Worthy of mention is the analysis of European foreign exchange markets by [22,20,23,24,25]. Similarly, [22] demonstrates that volatility spillovers exist among the central European foreign currency markets. According to [26], there is limited evidence of volatility spillovers between the US dollar and the German mark, the British pound, the Japanese yen, and the Swiss franc. [27] examine the return co-movement and volatility spillover between the currency markets of the BRICS and a few specific industrialized countries from 2006 to 2019. The findings demonstrate the existence of sizable return correlations and spillovers between the foreign currency markets in various nations. [18] studied volatility spillover and its interconnectivity in global foreign exchange markets. [28] has analysed connectedness between Asia-Pacific markets by giving special importance to China. [29] assessed volatility connectedness between the currencies of Central European (CE) countries from 2009 to 2022. They found that there are asymmetries in connectedness, particularly during periods of crisis. Similarly, [30] have analysed the spillovers among African countries during crisis periods and the study found a low system-wide spillover connectedness among them.

Against the backdrop of the increasing connectedness of economic activities across regions, the intra-regional integration of Asian foreign exchange markets has been a particular area of interest for financial researchers. Numerous studies have been conducted about the Asian foreign exchange

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1 One market’s volatility may spread to another, often persisting after that market closes and causing volatility in distant markets that open many hours later. Meteor shower is the term used to describe this phenomenon (Engle et al., 1990).

2 According to the “Heat wave Hypothesis” idea, a market’s volatility will persist the next day.

market and currency connectedness during different periods. [31] primarily examined how the Asian foreign exchange market has performed recently. The Asian foreign exchange market has significantly increased in depth and breadth in recent years. [32] in their study simulated the co-movements of exchange rate changes and news sentiments of 14 Asian-Pacific currencies from 1998 to 2022 using [29] connectedness technique. According to them, exchange rate fluctuations become more interconnected over time, particularly among developed nations following the GFC. All of them have ignored the behaviour of forex markets during extreme events, both in the time and frequency domains. The activity of Asian currencies remained significantly more concentrated in onshore markets, proving that the interconnectedness between the currencies has grown recently. For example, [33] in their study on exchange rate volatility spillover that focused on the interdependence among the major exchange rates around the world, especially in Central Asia, discovered a positive dependence between these exchange rates. [34] for instance, tries to estimate a multivariate Dynamic Conditional Correlation (DCC) model for estimating the interdependence between the exchange rate of the Indian Rupee and the other four well-known foreign currencies. The empirical findings show that each of these exchange rates frequently exhibits substantial levels of volatility clustering.

Only a few research studies have looked at the interaction and connectedness between the currencies during crisis and tranquil times, particularly across different economies in the backdrop of a highly integrated foreign exchange market. There will be a high level of uncertainty in the foreign exchange market during shocks or crises. It can lead to a high level of volatility spillover and returns spillover among the currency exchange rates. The GFC (2008) has drawn great attention to connectedness within the foreign exchange market, reminding us that connectedness is of critical importance to macroeconomic stability, yet still poorly defined and measured. [35] address the connectedness between global foreign exchange markets during the COVID-19 crisis. Their findings indicate a high degree of interdependence between the COVID-19 shock and return volatility for the majorly traded currency pairs. Accordingly, currencies in the foreign exchange markets transmit risks to and receive risks from other currencies. [36] in their study reveals that during financial crises, currencies form contagions and they cluster in both positive and negative directions. The daily return connectivity pattern shows that currencies in developed economies are net shock transmitters (receivers) in terms of time-domain spillover. As a result, studying connectedness among global currencies in different periods is very important. However, this study differs from theirs by examining spillovers and volatility transmissions between eight major currencies in the Asian foreign exchange market during two important crises: the GFC (2008) and the COVID-19 crisis.

Coming to the earlier empirical literature on interdependencies in Asian economies' exchange rate markets has largely relied on copulas [12], wavelets [15], and cross-correlation [17]. GARCH models [13]. The return spillovers under extreme circumstances are not captured by conventional approaches, despite their well-known usefulness. This is particularly helpful for investors and policymakers who are primarily concerned with the interdependencies among exchange rates both on average and during exceptional events.

By focusing more on the eight important Asian currencies, the study contributes to the existing literature in the following ways. There are fewer studies about the interconnectedness between currencies in the Asian Foreign exchange market in terms of the time and frequency domains. For example, [3] concentrates his work on the interconnection between Asian currency and equity markets. Many studies have looked at the co-movement of either equities or currency markets across

Asian economies. However, little attention is paid to the interdependence of currencies during crises and tranquil times, especially in the context of the Asian foreign exchange market. Shedding a new light on the interdependence between currencies is particularly important for two main reasons. First, Asian economic integration has been driven by trade linkages, which critically hinge on intra-regional exchange rate dynamics that affect the economic growth of a region. Second, the recent progress in foreign exchange market dynamics and the enhanced flexibility in exchange rate systems in the region have generated a new channel of cross-interdependence across different Asian economies. Thus, it is essential to pay attention to this to better evaluate the region-wide connectedness of major currencies and identify the underlying risk of financial contagion under extreme events.

### 3. Materials and Methods

For the empirical estimation of the model, daily foreign exchange returns of eight major currencies in the Asian foreign exchange markets are considered for this study. The currencies taken for the study are Yen, Yuan, Won, Rupees, Ringgit, Baht, Singapore Dollars, and Hong Kong Dollars (JPY: Yen, RMB: Yuan, KRW: Won, INR: Rupees, MYR: Ringgit, SGD: Singapore dollars, THB: Baht, HKD: Hong Kong Dollars). These eight major currencies are chosen based on the daily returns data availability of time from 2005-2024. It mainly focuses on connectedness in different quantiles in the Asian foreign exchange market during two crises: the GFC (2008) and the COVID-19 crisis. Daily foreign exchange returns are calculated as the logged differences of currency exchange rates of two consecutive days. Data are collected from the US FRED database.

#### 3.1. Empirical Methodology

The study uses the QVAR method throughout the entire sample, as opposed to estimating the TVP-VAR model over rolling sample windows. In this paper, it computes at each quantile, following the work by [37]. Thus, this paper focuses on the QVAR-based connectedness approach, which extends the connectedness approach by [11]. To calculate all connectedness metrics, first estimate a quantile vector autoregression, QVAR(p), which can be outlined as follows:

$$x_t = \mu(\theta) + \sum_{k=1}^p \varphi_k(\theta)x_{t-k} + \mu_t(\theta) \tag{1}$$

where  $x$  and  $x_{t-1}$  represent  $m \times 1$  vectors and  $p$  stands for the lag length of the QVAR model.  $\mu(\theta)$  is  $m \times 1$  dimensional conditional mean vector, whereas the  $\varphi_k(\theta)$  is an  $m \times m$  QVAR coefficient matrix and  $\mu_t(\theta)$  denotes the  $m \times 1$  dimensional error vector which has an  $m \times m$  variance-covariance matrix,  $\Sigma(\theta)$ . To transform the QVAR(p) into its moving average process which is QVMA( $\infty$ ), Wold's theorem is employed where,  $x_t = \mu(\theta) + \sum_{k=1}^p \varphi_k(\theta)x_{t-k} + \mu_t(\theta) = \mu(\theta) + \sum_{i=0}^{\infty} \rho_i(\theta)\mu_{t-i}$ . Afterwards, the H-step ahead Generalised Forecast Error Variance Decomposition (GFEVD) of [38] and [39] is calculated, which illustrates the impact a shock in variable  $j$  has on variable  $i$ :

$$\rho_{ij,t}^g(H) = \frac{\sum_{h=0}^{H-1} \sum_{i=0}^{H-1} (e_i' \rho_h(\theta) \Sigma(\theta) e_j)^2}{\sum_{h=0}^{H-1} (e_i' \rho_h(\theta) \Sigma(\theta)' e_j)} \tag{2}$$

$$\rho_{ij}^{\sim g}(H) = \frac{\rho_{ij,t}^g(H)}{\sum_{j=1}^k \rho_{ij,t}^g(H)} \tag{3}$$

##### 3.1.1. Directional Spillovers

The Generalized VAR approach enables us to learn about the direction of spillovers across major foreign exchange currency classes. As the generalized impulse responses and variance decompositions are invariant to the ordering of variables, the directional spillovers are calculated using the normalized elements of the generalized variance decomposition matrix. The directional spillovers transmitted by market  $i$  TO all other markets  $j$  as:

$$To_{ij} = \sum_{j=1, i \neq j}^k \rho_{ji}^g(H) \quad (4)$$

$$i=1, i \neq j$$

The Directional spillovers received by market  $i$  FROM all other markets  $j$  as:

$$From_{ij} = \sum_{j=1, i \neq j}^k \tilde{\rho}_{ij}^g(H) \quad (5)$$

$$i=1, i \neq j$$

Equation (4) estimates the total impact a shock in sector  $j$  has on all other sectors, which is defined as the total directional connectedness to others. These are the set of directional spillovers as providing a decomposition of the total spillovers to those coming from (or to) a particular source. Equation (5), on the other hand, estimates the total influence all other sectors have on variable  $j$ , which is defined as the total directional connectedness from others.

### 3.1.2. Net Spillovers

To obtain the net spillover from market  $j$  to all other markets  $t$  can be found by using the following equation.

$$Net_{jt} = To_{jt} - From_{jt} \quad (6)$$

Equation (6) is the difference between equations (4) and (5), which gives the net total directional connectedness, which tells us whether a sector is a net transmitter or a net receiver of shocks.

### 3.1.3. Total connectedness index and corrected connectedness index

The Total Connectedness Index (TCI) shows the connectedness between all the currency exchange rate returns, which is the average impact of all the spillovers between the exchange rates. The equation below shows the estimation of TCI.

$$TCI_t = \frac{1}{k} \sum_{j=1}^k To_{jt} = \frac{1}{k} \sum_{j=1}^k From_{jt} \quad (7)$$

A high TCI for the overall market implies stronger interconnectedness between the currencies. Another essential connectedness measure represents the Corrected Connectedness Index (CCI), which can be described as the average impact one variable has on all others. If this measure is relatively high, it implies that the interconnectedness of the network and hence the market risk is high and vice versa. The equation below can compute the CCI:

$$CCI_t = (k - 1)^{-1} To_{jt} \equiv k^{-1} From_{jt} \quad j = 1 \quad (8)$$

This connectedness measure focuses on the time domain approach. Now the paper looks into the frequency domain connectedness measure. The study employs the methodology developed by [40] to assess the quantile connectedness of the Asian foreign exchange market over both short and long spectral timescales. This involves employing the method of frequency quantile connectivity. We DOI: <https://doi.org/10.54560/jracr.v15i3.608>

can record the connection component in the frequency domain by using the spectral response function.  $\phi(e^{-i\omega}) = \sum_{h=0}^{\infty} (e^{-i\omega h}) \phi_h$  with  $i = \sqrt{-1}$  where  $\omega$  is the frequency term. Now the spectral density is derived on  $x_t$  and can be defined as the Fourier transform of QVAR

$$Q_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x_{t-h}) e^{-i\omega h} = \phi(e^{-i\omega}) \sum_t \phi'(e^{+i\omega}) \tag{9}$$

Equation 10 indicates the generalized forecast error variance decomposition (GFEVD)

$$\phi_{ij}(\omega) = \frac{\sum(\tau)_{jj}^{-1} \sum_{h=0}^{\infty} (\phi(\tau)(e^{-i\omega h}) \sum(\tau))_{ij}^2}{\sum_{h=0}^{\infty} (\phi(\tau)(e^{-i\omega h}) \sum(\tau)\phi(\tau)(e^{-i\omega h}))_{ii}} \tag{10}$$

Since  $\phi_{ij}(\omega)$  's rows don't add up to 1, it can be normalized as follows:

$$\tilde{\phi}_{ij} = \frac{\phi_{ij}(\omega)}{\sum_{i=1}^N \phi_{ij}(\omega)} \tag{11}$$

Here  $\sum_{i=1}^N \tilde{\phi}_{ij}(\omega) = 1$  and also the term  $\sum_{i=1}^N \tilde{\phi}_{ij}(\omega) = N$ .  $\tilde{\phi}_{ij}(\omega)$  estimates the section of the variable  $i$ 's spectrum at frequency  $\omega$  that corresponds to a shock in variable  $j$ . Instead of evaluating connectedness at a single frequency, all of the values at  $\tilde{\phi}_{ij}(\omega)$  frequencies within a certain range  $d = (a, b)$ :  $a, b \in (-\pi, \pi)$ ,  $a < b$ , are aggregated to obtain  $\tilde{\phi}_{ij}(d) = \int_a^b \tilde{\phi}_{ij}(\omega) d\omega$  whether evaluating short- or long-term connectedness. The net pairwise directional connectedness (NPDC) index could be defined using the  $\tilde{\phi}_{ij}(d)$  as

$$NPDC_{ij}(d) = [\tilde{\phi}_{ij}(d) - \tilde{\phi}_{ji}(d)] \tag{12}$$

Variable  $i$  dominates variable  $j$  if  $NPDC_{ij}$  is less than zero, which shows that variable  $j$  influences variable  $i$  more than vice versa. The amount of a shock in variable  $i$  that is transferred to others is measured by the total directional connectivity to others (TO), which is measured as

$$TO_i(d) = \sum_{j=1, j \neq i}^N \tilde{\phi}_{ij}(d) \tag{13}$$

In the same way, the total directional connectivity from others (FROM), which quantifies the amount of variable  $i$  receive from shocks in other variables are estimated by the following equation

$$FROM_i(d) = \sum_{j=1, j \neq i}^N \tilde{\phi}_{ji}(d) \tag{14}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{15}$$

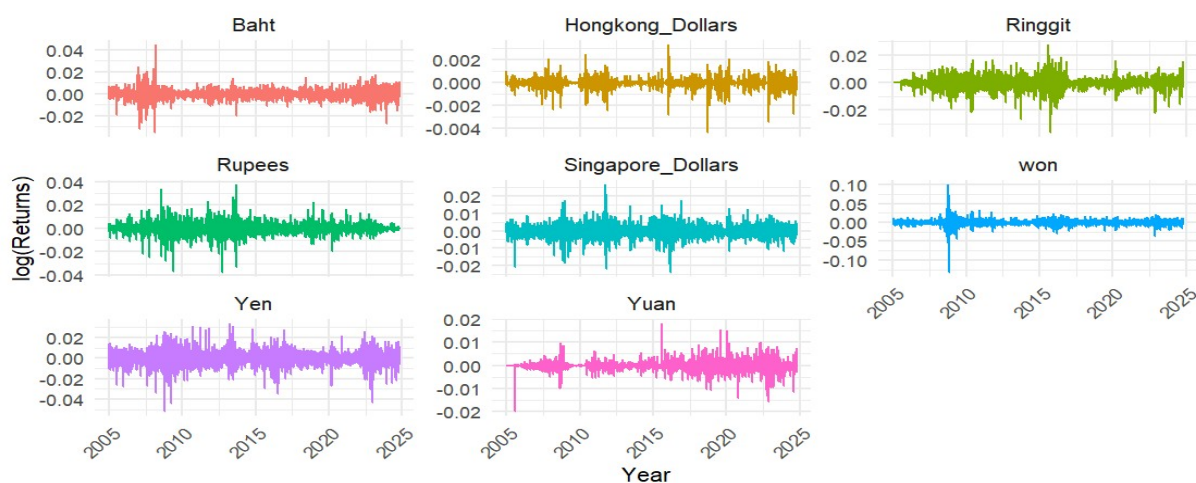
Equation 15 shows the net total directional connectedness estimation, and the way to understand the  $NET_i(d)$  is as the influence that variable  $i$  has on the system under investigation. In the event where  $NET_i(d) > 0$  ( $NET_i(d) < 0$ ), it shows that variable  $i$  has a greater or lesser impact on the system under investigation than it does on itself. It is therefore thought of as a net shock transmitter or receiver. The formula for the total connectedness index (TCI), which gauges the degree of system interconnection, is as follows;

$$TCI(d) = N^{-1} \sum_{i=1}^N TO_i(d) = N^{-1} \sum_{i=1}^N FROM_i(d) \tag{16}$$

#### 4. Results and Discussion

Figure 1 below shows the return series plots of the eight major currencies in the Asian foreign exchange market from 2005 to 2025. The return series plots capture the volatility and shock behavior

of the foreign exchange markets over the period, with notable spikes during the global uncertainties. Figure 1 serves as the basis for analyzing the asymmetric spillovers using the QVAR connectedness approach, for capturing the spillovers in normal and extreme market conditions.



**Figure 1.** Return series plots for the currencies.

#### 4.1. Static Quantile Time Connectedness Results

Table 1 shows the connectedness in returns at the median level, where  $\theta = 0.5$ . From Table 1, it is clear that Singapore is the biggest transmitter and receiver of shocks from other currencies. After Singapore dollars, the Won is the second largest transmitter and receiver of shocks in the Asian foreign exchange market (in terms of returns). The Total Connectedness Index (TCI) for returns appears in the lower right corner of Table 1, which indicates that, on average, across the entire sample, 31.60% of the forecast error variance in all eight foreign exchange markets comes from spillovers. The summary of Table 1 is simple: both the total and directional spillovers over the full sample period are quite low.

The results of the tail connectedness estimates are reported in Table 2 and Table 3, respectively, for the lower quantile ( $\theta = 0.1$ ) and upper quantile ( $\theta = 0.9$ ). This will distinguish between negative and positive shocks in the Asian forex market. For the left and right tail connectedness, the values are more than the middle quantile ( $\theta = 0.5$ ). This indicates the high level of impacts of negative and positive shocks on connectedness. The contribution to others and contributions from others are also higher than in the lower and upper quantiles compared to the middle quantile. In the lower quantile, 66.40% is TCI, and in the upper quantile, it is 79.89%. Both values are more than the middle quantile. In the lower quantile, the Singapore dollar appears to be highly connected with others, and in the higher quantile, Singapore dollars and Hong Kong dollars appear to be highly connected. From the static analysis, it is clear that the Singapore dollar is a highly connected currency in the Asian foreign exchange market. The results validate the arguments made [41] in their study about the quantile connectedness in the Asia-Pacific context. They point out that the rise in the reactivity of the connectedness index rates to both extreme positive and extreme negative return shocks is high at both the left and right tails. This asymmetric pattern indicates that shocks are not uniformly transmitted across Asian foreign exchange markets, but are more evident during stress episodes. The increased connectivity in the tails is consistent with the crisis-contingent contagion theory, which

holds that the lack of confidence in the market strengthens market co-movements and interdependencies during financial turbulence

**Table 1.** Connectedness Measures at Median quantile  $\theta = 0.5$ .

	JPY	RMB	KRW	INR	MYR	SGD	THB	HKD	FROM
JPY	73.02	3.23	3.92	2.51	2.66	8.46	3.95	2.26	26.98
RMB	3.22	73.04	4.29	2.56	4.44	6.51	3.61	2.32	26.96
KRW	3.85	4.17	60.98	3.90	7.63	10.68	6.21	2.58	39.02
INR	2.66	3.09	4.20	72.22	4.59	7.05	3.78	2.41	27.78
MYR	2.53	4.61	7.71	4.00	65.68	8.14	5.15	2.17	34.32
SGD	6.86	5.28	9.03	5.22	6.80	55.28	9.32	2.20	44.72
THB	3.65	3.92	5.90	3.31	4.65	10.78	65.96	1.83	34.04
HKD	2.49	2.88	3.00	2.28	2.67	3.28	2.39	81.00	19.00
TO	25.26	27.19	38.05	23.78	33.43	54.90	34.42	15.78	252.81
Inc. Own	98.28	100.23	99.04	96.00	99.11	110.18	100.38	96.78	cTCI/ TCI
NET	-1.72	0.23	-0.96	-4.00	-0.89	10.18	0.38	-3.22	36.12/ 31.60
NPT	2.00	5.00	5.00	0.00	3.00	7.00	5.00	1.00	

**Table 2.** Connectedness Measures at lower quantile  $\theta = 0.1$ .

	JPY	RMB	KRW	INR	MYR	SGD	THB	HKD	FROM
JPY	33.64	7.99	10.42	8.78	9.06	12.92	10.10	7.09	66.36
RMB	8.42	37.62	9.52	8.09	9.68	10.74	9.06	6.88	62.38
KRW	9.49	8.11	30.28	9.50	11.78	13.21	10.55	7.08	69.72
INR	8.90	7.71	10.68	34.06	10.16	12.00	9.84	6.66	65.94
MYR	8.53	8.68	12.37	9.47	32.07	12.03	10.04	6.81	67.93
SGD	11.01	8.67	12.39	10.03	10.86	28.21	12.32	6.52	71.79
THB	9.55	8.13	11.00	9.13	9.98	13.68	32.03	6.50	67.97
HKD	8.55	7.49	9.28	7.91	8.61	9.15	8.14	40.88	59.12
TO	64.44	5677	75.66	62.91	70.11	83.73	70.05	47.55	531.22
Inc. Own	98.08	94.39	105.94	96.97	102.18	111.93	102.08	88.42	cTCI/ TCI
NET	-1.92	-5.61	5.94	-3.03	2.18	11.93	2.08	-11.58	75.89/ 66.40
NPT	3.00	1.00	6.00	2.00	4.00	7.00	5.00	0.00	-

**Table 3.** Connectedness at upper quantile  $\theta = 0.9$ .

	JPY	RMB	KRW	INR	MYR	SGD	THB	HKD	FROM
JPY	20.40	10.76	11.30	10.38	10.96	12.36	11.24	12.62	79.60
RMB	11.26	20.07	11.50	10.23	11.42	11.73	10.87	12.92	79.93
KRW	11.11	10.59	19.25	10.46	11.94	12.89	11.43	12.34	80.75
INR	10.79	10.48	11.99	19.61	11.72	12.19	11.31	11.91	80.39
MYR	10.81	11.01	11.99	10.92	19.30	12.46	11.33	12.20	80.70
SGD	11.67	10.59	12.33	10.72	11.64	19.23	11.91	11.90	80.77
THB	11.10	10.67	11.73	10.68	11.47	12.52	19.80	12.05	80.20
HKD	11.28	11.08	11.35	10.13	11.04	11.47	10.47	23.19	76.81
TO	78.01	75.17	82.18	73.50	80.18	85.61	78.56	85.94	639.16
Inc. Own	98.41	95.24	101.43	93.11	99.48	104.84	98.36	109.13	cTCI/ TCI
NET	-1.59	-4.76	1.43	-6.89	-0.52	4.84	-1.64	9.13	91.31/ 79.89
NPT	2.00	1.00	5.00	0.00	4.00	6.00	3.00	7.00	-

#### 4.2. Dynamic Connectedness Results

##### 4.2.1. Spillover Plots

The full sample spillover tables and spillover indexes that were previously acquired offer a helpful summary of “average” behaviour among the currencies, but they do not effectively capture the dynamic nature of such spillovers in detail. The connectedness tables likely have missed the potentially significant secular and cyclical spillover fluctuations across the years, particularly during the period of crises. To address this issue, this paper assesses the extent and nature of spillover variation over time using spillover plots. It examines graphically the total spillover plots for returns using QVAR, which can effectively capture the dynamic nature of the spillovers of the currencies. Figures 2,3, and 4 show the total spillover plot for returns in three quantiles. This allows for a deeper understanding of the exchange rate spillovers under different market conditions during stress and tranquil periods.

The spillover plots, which graphically represent the TCI and NET directional spillovers over time across different quantiles of the return distribution, provide insights into how spillovers behave over the years. Figures 2, 3, and 4 present the total spillover plots at three quantile levels: the lower ( $\theta = 0.1$ ), median ( $\theta = 0.5$ ), and upper ( $\theta = 0.95$ ) quantiles, corresponding to extreme negative shocks, average market conditions, and extreme positive shocks, respectively. By examining these plots, the study investigates whether connectedness intensifies asymmetrically during periods of financial turmoil compared to normal periods.

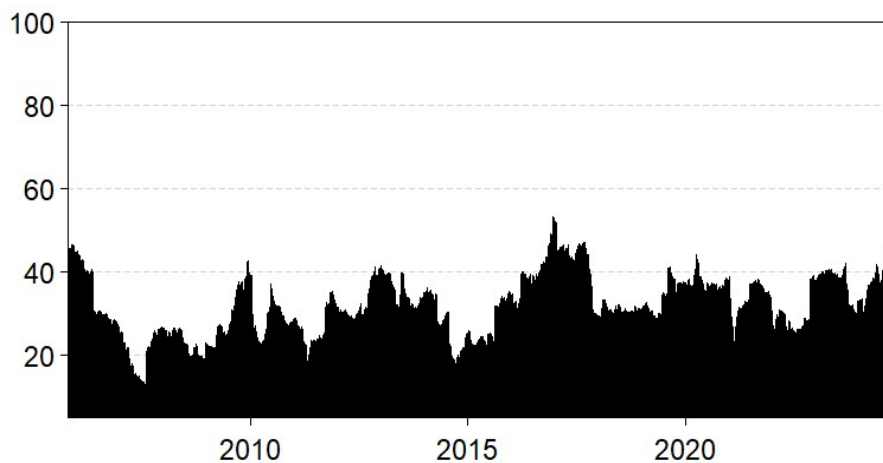


Figure 2. Total Spillover Plots (Returns),  $\theta = 0.5$ .

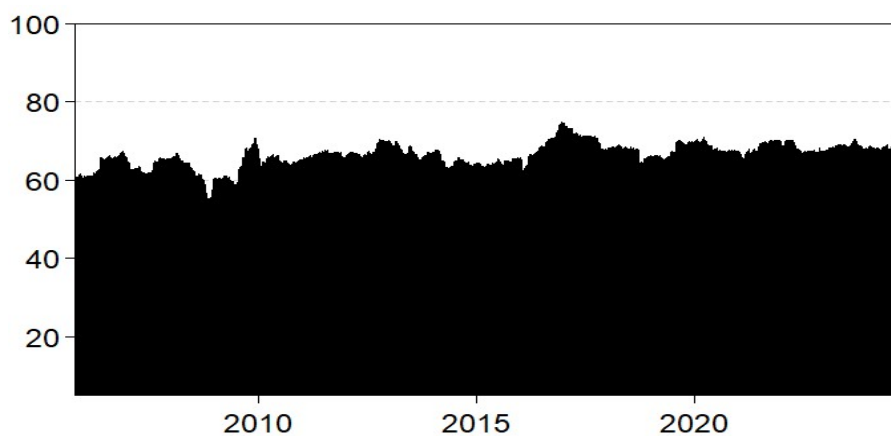


Figure 3. Total Spillover Plots (Returns),  $\theta = 0.1$ .

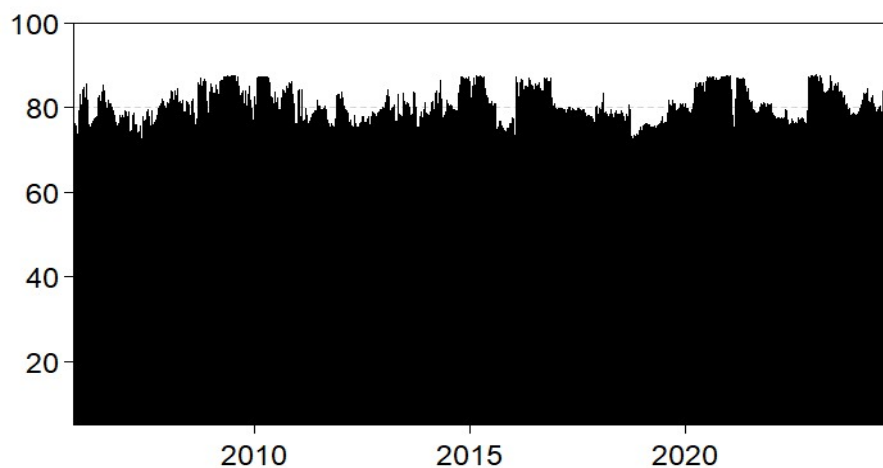


Figure 4. Total Spillover Plots (Returns),  $\theta = 0.9$ .

Figure 2 presents the spillover plot for returns in the median quantile, which varies between 20-50%. However, the spillover plots for  $\theta = 0.1$  and  $\theta = 0.9$  at both the left and right tails (respectively shown in Figure 3 and Figure 4) are much higher, but the range of fluctuations is much lower, varying

between 60% and 80%. Such a large level of connectedness in the returns at both left and right tails suggests an increase in the sensitivity of Asian currencies to both extreme negative and extreme positive return shocks. Thus, the spillover plots suggest that interdependencies among Asian currencies are much more prominent during extreme negative and positive return shocks. The uncertainties in the financial market cause greater and more coordinated reactions among regional foreign currency markets because of the high level of connectedness in the tails, which represents increased market sensitivity and co-movement under stress situations. These results complement the findings of [12,41,13,14], where they also found strong connectedness in upper and lower quantiles, which shows a contagion effect during extreme situations.

#### 4.2.2. Net Directional Spillover Plots

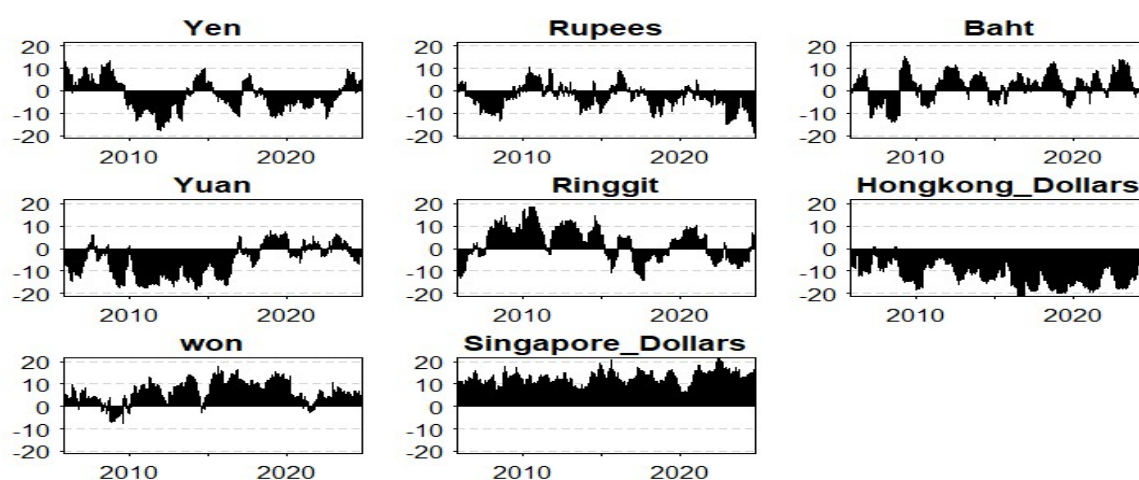


Figure 5. Net Spillover Plot,  $\theta = 0.1$ .

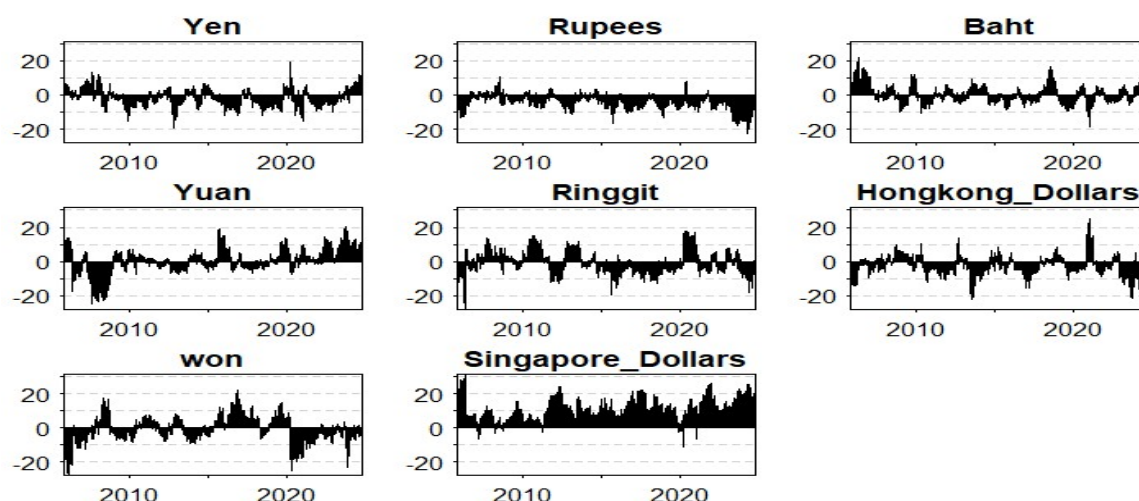


Figure 6. Net Spillover Plot,  $\theta = 0.5$ .

The net directional spillover is the difference between the “Contribution from” (column sum) and the ‘Contribution to’ (row sum). The figures below show net directional spillover in lower, middle, and upper quantiles. Here, a positive net spillover indicates that a currency is a net

transmitter of shocks, while a negative value suggests it is a net receiver of shocks. Figures 5,6,7 illustrate the net directional spillovers in the lower ( $\theta = 0.1$ ), middle ( $\theta = 0.5$ ), and upper ( $\theta = 0.9$ ) quantiles, respectively. These plots provide insights into the role of each currency in the spillover network and how it changes across different market conditions. Comparing these quantiles, the study provides insights into which currencies are more dominant transmitters or receivers during times of market stress.

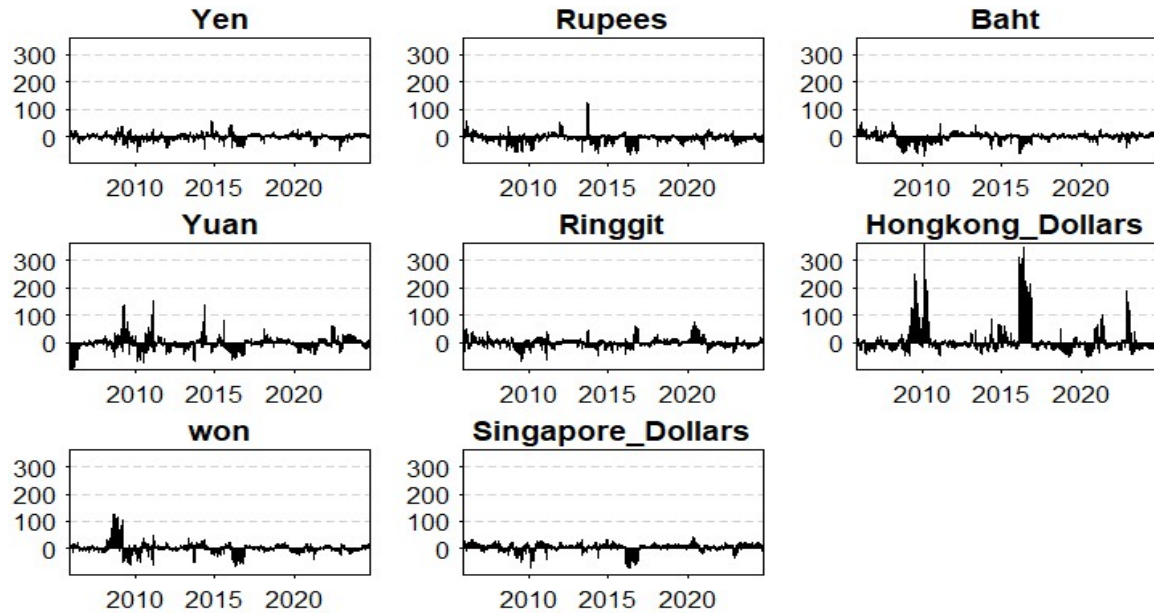


Figure 7. Net Spillover Plot,  $\theta = 0.9$ .

The currencies show different patterns in terms of returns spillovers in different quantiles. That is, it shows if a sector is a net transmitter to or a receiver of shocks from other sectors. In the lower quantile (shown in Figure 5), the Singapore dollar is the only currency that is a net transmitter of the shocks in extreme events, and the Hong Kong dollar is the net receiver of shocks as well. However, the spillover over a period varies. Fig.6 shows the net directional spillover plot for the middle quantile. It also indicates Singapore dollar is a net transmitter of the shocks to other currencies. But in the upper quantile, Hong dollars become net transmitters of the shocks and Singapore dollars become net receivers of the shocks. Accordingly, investors and regulators should closely monitor these two transmitters if the historical pattern underlined by the network of connectedness at the median continues into the future. However, when there are extreme events, marked by the upper and lower quantiles, the behaviour of the net spillovers becomes different, and it follows that, under extreme events, investors and policymakers should continuously follow the dynamic net spillovers of returns shocks in the Asian foreign exchange market. This also validates the study by [41], where they argue that under extreme events in the Asian foreign exchange market, the currency returns behave in a different way. Thus, they show the evidence of asymmetry and its presence during extreme events. These results align with [42], where they argue that spillovers across currency markets intensify during distress periods. The results also complement previous studies [12,13,14,15].

#### 4.3. Static Quantile Frequency Connectedness

As discussed above, the time-domain connectedness captures the overall level of spillovers at a given quantile, whereas the frequency-domain decomposition distinguishes between short-term (high-frequency) and long-term (low-frequency) components of connectedness. This distinction is particularly important because the short-term connectedness is often driven by market sentiments, whereas the long-term connectedness reflects more persistent structural linkages in the market. This section deals with the connectedness in the frequency domain, which captures the effects of the extreme shocks affecting spillovers (through quantiles), over different horizons. Table 4 shows the static quantile frequency connectedness estimates, and the short- and long-term connectivity values are enclosed in parentheses.

By analysing both time and frequency domains within the quantile framework, the study captures not only how extreme shocks affect spillovers (through quantiles), but also how these spillovers propagate over different horizons. As an example, we discover that the Hong Kong dollar exhibits the largest own-variance share spillovers, at 81%. 56.82% of the 81% are thought to be short-term own-variance spillovers, whereas 24.18% are long-term ones. This indicates that 19% of the forecast error variance of the Hong Kong Dollars is attributable to the others. This currency is specifically impacted by Singapore Dollars and Won. Among the Asian currencies Rupee is the major receiver of the shocks in the forex market (-4.00%), and the Singapore Dollar is the major transmitter of the shocks to other currencies (10.18%). Considering the short-term spillover, the Rupee is the main net receiver of the shocks, and the Singapore dollar is the main transmitter of the shocks. A similar trend can be observed in the long term as well. Thus, we can say that the Singapore dollar is a strong currency that transmits shocks to other currencies and receives them.

**Table 4.** Connectedness in terms of Frequency.

-	JPY	RMB	KRW	INR	MYR	SGD	THB	HKD	FROM
<b>JPY</b>	73.02 (56.8, 16.1)	3.23 (2.26, 0.97)	3.9 (2.89, 1.02)	2.51 (1.77, 0.73)	2.66 (1.81, 0.84)	8.41 (6.41, 2.05)	3.95 (2.9, 5.1)	2.26 (1.5, 0.76)	26.98 (19.61, 7.37)
<b>RMB</b>	3.22 (2.22, 1.01)	73.0 (52.32, 20.73)	4.29 (3.12, 1.17)	2.56 (1.8, 0.77)	4.44 (2.99, 1.45)	6.51 (4.65, 1.86)	3.61 (2.59, 1.02)	2.32 (1.49, 0.840)	26.96 (18.84, 8.11)
<b>KRW</b>	3.85 (2.65, 1.19)	4.17 (3.11, 1.05)	60.98 (47.36, 13.62)	3.90 (2.91, 0.99)	7.63 (5.56, 2.07)	10.68 (7.81, 2.87)	6.21 (4.45, 1.75)	2.58 (1.73, 0.85)	39.02 (28.23, 10.79)
<b>INR</b>	2.66 (1.78, 0.87)	3.09 (2, 1.09)	4.20 (3.17, 1.03)	72.22 (54.17, 18.04)	4.59 (3.3, 1.29)	7.05 (5.07, 1.98)	3.78 (2.87, 0.92)	2.41 (1.58, 0.82)	27.78 (19.77, 8.01)
<b>MYR</b>	2.53 (1.59, 0.94)	4.61 (2.97, 1.64)	7.71 (5.72, 1.99)	4.00 (2.91, 1.09)	65.68 (49.59, 16.09)	8.14 (5.68, 2.46)	5.15 (3.59, 1.57)	2.17 (1.47, 0.71)	34.32 (23.93, 10.39)
<b>SGD</b>	6.86 (5.32, 1.54)	5.28 (4.12, 1.17)	9.03 (7.04, 20)	5.22 (4.05, 1.17)	6.80 (5.05, 1.74)	55.28 (43.85, 11.43)	9.32 (7.12, 2.2)	2.20 (1.66, 0.550)	44.72 (34.36, 10.36)

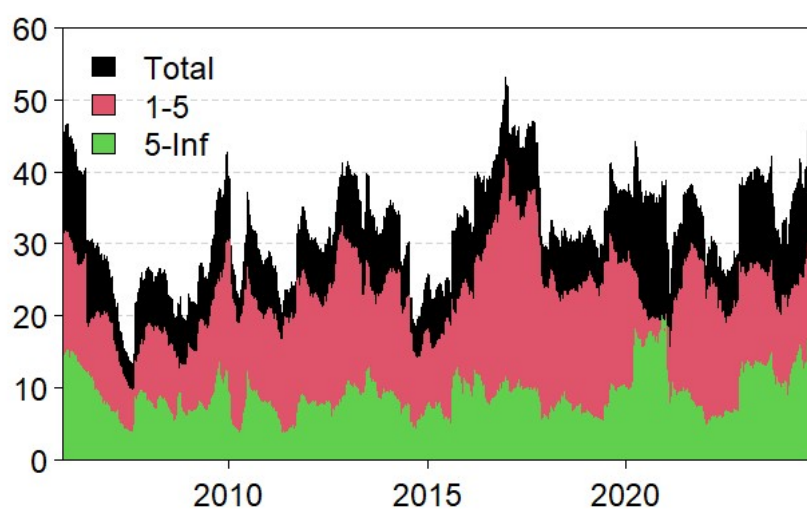
<b>THB</b>	3.65 (2.73, 0.92)	3.92 (2.71, 1.21)	5.90 (4.49, 1.41)	3.31 (2.55, 0.76)	4.65 (3.53, 1.11)	10.78 (8.33, 2.44)	65.96 (50.47, 15.5)	1.83 (1.29, 0.54)	34.04 (25.65, 8.39)
<b>HKD</b>	2.49 (1.55, 0.94)	2.88 (1.71, 1.7)	3.00 (2, 1)	2.28 (1.57, 0.71)	2.67 (1.69, 0.98)	3.28 (2.16, 1.12)	2.39 (1.57, 0.82)	81.00 (56.82, 24.18)	19.00 (12.25, 6.75)
<b>TO</b>	25.26 (17.85, 7.41)	27.19 (18.89, 8.3)	38.05 (28.43, 9.62)	23.78 (17.55, 6.23)	33.43 (23.9, 9.49)	54.90 (40.11, 14.78)	34.42 (25.15, 9.28)	15.78 (10.72, 5.06)	252.81 (182.64, 70.17)
<b>Inc. Own</b>	98.28 (74.68, 23.6)	100.2 (71.2, 29.03)	99.04 (75.79, 23.25)	96.00 (71.73, 24.27)	99.11 (73.5, 25.58)	110.18 (83.9, 26.22)	100.38 (75.62, 24.76)	96.78 (67.54, 29.64)	cTCI/T CI
<b>NET</b>	-1.72 (-1.77, 0.04)	0.23 (0.05, 0.18)	-0.96 (0.2, - 1.17)	-4.00 (-2.22, - 1.78)	-0.89 (0.01, - 0.9)	10.18 (5.76, 4.42)	0.38 (-0.5, 0.89)	-3.22 (-1.53, - 1.69)	36.12/31 .60 (26.09/2 2.8, 10.02/8. 77)
<b>NPT</b>	2.00 (2.00, 5.00)	5.00 (4.00, 4.00)	5.00 (6.00, 3.00)	0.00 (0.00, 0.00)	3.00 (4.00, 3.00)	7.00 (7.00, 7.00)	5.00 (4.00, 5.00)	1.00 (1.00, 1.00)	-

Notes: The results are based on a 200-day rolling-window QVAR model with a 100-step-ahead generalized forecast error variance decomposition and a lag length of order 1 (BIC). All-other values are the time connectedness measures, whereas the first and second values in parenthesis () stand for short- and long-term frequency connectedness measures, respectively.

#### 4.3.1. Median Dynamic Quantile Frequency Connectedness

The figure given below shows the median quantile connectedness in the frequency domain. I begin by examining the total connectedness index at the median quantile shown in Fig. 8. Throughout the sample period, it appears that TCI at the median quantile fluctuates around 40% to 50%. In specifics, both TCIs dropped from about 40% to 10% during the GFC and 50% to 20% during the COVID-19 crisis. Following the COVID-19 pandemic, the world has been marked by significant market volatility, a cessation of regular daily operations, and a great deal of uncertainty [43]. Understanding the patterns across various investment horizons is also crucial for investors and policymakers. The frequency analysis shows that over the majority of the sample period, the short-term and long-term TCIs act similarly; nonetheless, the short-term dynamics are primarily responsible for the TCI changes. The long-term value touched its peak after 2020 (the outbreak of the COVID-19 pandemic period); on the other hand, the short-term value reached its peak in 2016. This is the period where the total TCI value also touched the maximum. There is a clear dominance of short-term on total TCI compared to long-term TCI in the Asian foreign exchange market. This is crucial for risk managers and investors because a significant shift in the long-term TCI typically indicates that the entire market structure has changed significantly [3]. This analysis underscores the superiority of the QVAR approach in the case of outliers and the significance of breaking down the

total TCI into short-term and long-term TCI to increase the explainability of the total TCI's movements. These results are in line with the findings of [40].



**Figure 8.** TCI Frequency Connectedness.

Note: The short-term and long-term TCI are shown by the red and green areas, respectively, while the overall TCI is shown by the black area

#### 4.3.2. Measures of Median Net Total Directional Connectedness

In the research on connectivity, the findings about each series' net transmission power are highly significant. In this particular instance, it provides crucial information for investors and the management of risks. I discovered that each of the eight series of being a net sender or recipient of shocks is entirely due to long-term dynamics when we broke down the net total directional connectedness into short-term and long-term dynamics. In contrast, the short-term net transmission mechanism provides a very clear picture. These results are shown in Figure 9. In addition to the fact that black-shaded area results correspond to total connectedness, green-shaded and black-shaded results break down the analysis into short-run and long-run connectedness results, respectively, dynamic analysis suggests that the variables of the network may shift roles over time, and positive values correspond to net transmitters of shocks into the system and negative values to net receivers of shocks. In this analysis, all currencies except Singapore dollars exhibit the characteristic of net transmitter of the shocks to other currencies, and it becomes only a net receiver of shocks by long-run dynamics. All other currencies show mixed evidence of being net transmitters and net receivers of shocks caused mainly by long-term dynamics. Therefore, while the short-term dynamics remain relatively constant over time, the long-term dynamics either increase or decrease a series' net transmission power, either receiving shocks or sending them out. Financial advisors and investors are particularly interested in this information because, while the short-term characteristics of being a transmitter and a receiver remain the same, it provides information about how the series affects the network or how the network affects the series and, consequently, the investment risk.

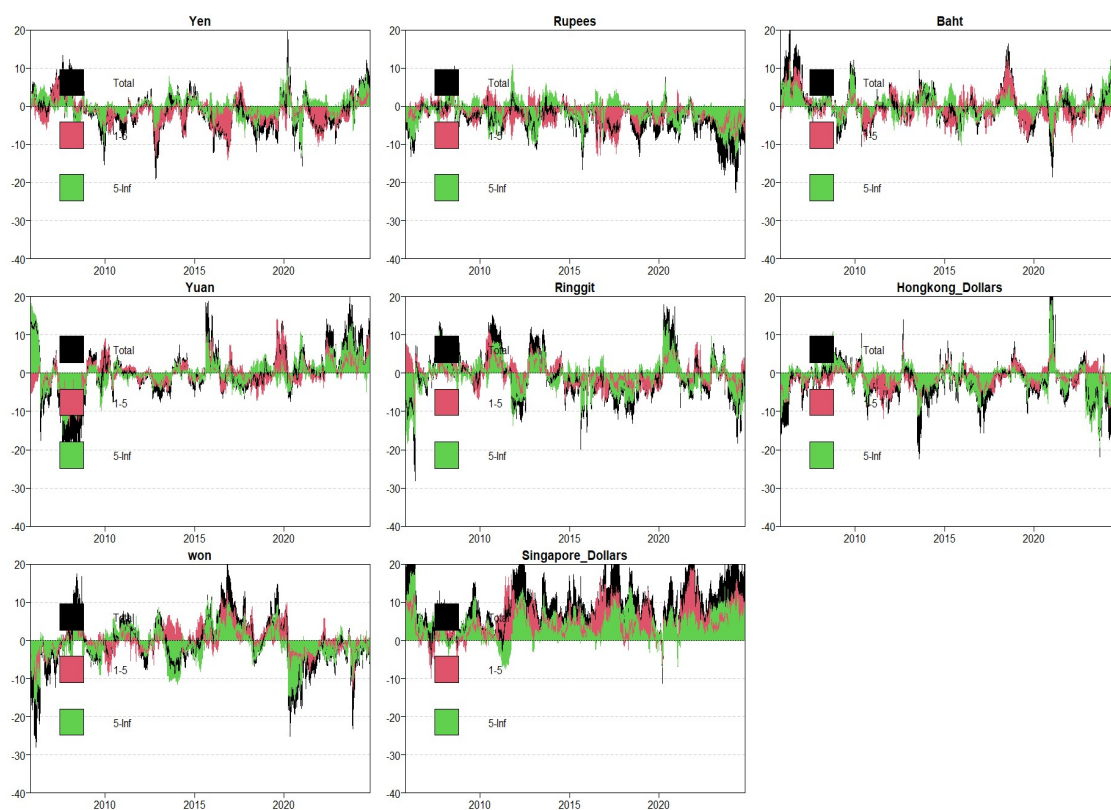


Figure 9. Overall, long-term and short-term directional connectivity.

Note: A QVAR model with a 200-day rolling window size, a 100-step-ahead generalized forecast error variance decomposition, and a lag length of order one (BIC) is the basis for the results. The time dynamic connectivity values are shown by the black region, and the short- and long-term outcomes are shown by the green and black areas.

## 5. Conclusion, Recommendations, and Policy Implications

This study applies quantile-based measures of return spillovers to analyse the network of connectedness in the Asian forex market by extending the approach of [11]. By examining daily exchange rate data from eight Asian economies, the paper finds significant variations in spillover effects across different parts of the conditional distribution. Specifically, return shocks exhibit stronger propagation in both the lower and upper tails compared to the conditional median, indicating heightened market interconnectedness during extreme events. This paper also contributes to the existing literature by analysing the connectedness by looking into the frequency as well. The paper employs the methodology developed by [37,40] to assess the quantile connectedness of the Asian foreign exchange market over both short and long spectral timescales. The results reveal that in the time domain approach, the Singapore dollar is a highly interconnected currency in the Asian foreign exchange market. This research supports the claims made by [44] that financial variables are more robust during stressful times than during regular times. The findings also support the claims made by [41] in their investigation of quantile connections in the Asia-Pacific region. They note that both the left and right tails greatly increase the connectedness index sensitivity to extreme positive and extreme negative return shocks. The findings underscore the importance of adopting quantile-based connectedness measures for a more comprehensive understanding of spillover dynamics in the Asian forex market. By capturing tail-specific dependencies, this approach provides deeper

insights into periods of heightened volatility and systemic risk, which are crucial for policymakers, investors, and market participants. Understanding the patterns across various frequency horizons is also crucial for investors and policymakers. The frequency analysis shows that over the majority of the sample period, the short-term and long-term TCIs act similarly; nonetheless, the short-term dynamics are primarily responsible for the TCI changes. So, it is evident that there is a clear dominance of short-term on total TCI compared to long-term TCI in the Asian foreign exchange market. This is crucial for risk managers and investors because a significant shift in the long-term TCI typically indicates that the entire market structure has changed significantly [44].

For future research, Wavelet Quantile Coherence (WQC) can be used for a more detailed understanding of market dependencies across different quantiles and time horizons. WQC helps policymakers and investors better assess systemic risks and formulate more effective strategies.

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