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U.S. Dollar Effect on Currency Interdependence: Case Study of Korean Won

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Abstract

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This study investigates how correlations between two trading currencies shift in response to changes in U.S. Dollar value. Focusing on the Korean Won and the currencies of its 20 largest trading partners, this paper models their pairwise time-varying dependence from 2006 to 2024. The analysis is conducted using static canonical vine copula models, which are subsequently extended for dynamic analysis using an auto-regressor, marginal distributions of monthly currency return, and change in USD. Our findings show that currency correlations are typically inflated by the USD, USD appreciation increases the correlation between two currencies, and currencies of more economically integrated countries tend to exhibit stronger dependencies during prolonged periods of dollar strength than those of less integrated economies.

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Minsol Kim

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1 Introduction

The establishment of the US dollar (USD) as the global reserve currency has provided the foundation for American political and financial dominance, offering crucial leverage in the global economy (Costigan et al., 2017). As of 2022, the USD accounted for 54% of global trade invoices (Boocker and Wessel, 2024). This "exorbitant privilege," as described by Canzoneri et al. (2017), ensures a steady stream of demand for USD, which allows the U.S. government to issue debt at lower interest rates and maintain large trade deficits without conventional short-term consequences. The dollar-centric financial system, however, carries significant risks for small-open economies whose liabilities are predominantly dollar-denominated. As documented by Eren and Malamud (2022), the USD is not the safest currency to hold debt over long horizons due to its tendency to depreciate after downturns, a higher inflation risk premium, and its strong correlation with global markets. Despite these risks, the USD remains the unrivaled choice for global debt issuance, as no other currency provides the same level of market liquidity, low issuance costs, or financial stability (Eren and Malamud, 2022).

However, the International Monetary Fund's Currency Composition of Official Foreign Exchange Reserves shows that the USD's share of global foreign exchange reserves has been steadily decreasing, from 71% of reserves in 2000 to 58% in 2024 (Bertaut et al., 2023). Global economies have been diversifying their reserves away from the traditional "big four" currencies—U.S. Dollar (USD), Japanese Yen (JPY), Great Britain Pounds (GBP), and Euro (EUR)—altogether. Instead, central banks and governments have been increasingly acquiring non-traditional currencies such as the Australian Dollar (AUD), Canadian Dollar (CAD), Chinese Renminbi (CNY), and Singaporean Dollar (SGD) to fill the reduced role of the USD (Arslanalp et al., 2024). The declining share of USD reserves alters the relationships between currencies, moving away from a system heavily influenced by a single "anchor" currency.

Jiang et al. (2022) demonstrates that a stabilized currency co-movement region develops from gradual multi-country exchange rate interactions. Supporting this theory, sub-networks of currencies were identified by removing the traditional 'core' currencies like USD and EUR from the network correlation structure. Mai et al. (2018) finds that while USD and EUR have a significant impact on the global FX network, the East Asian module exhibits an independent floating basis, indicating the emergence of a new stabilized currency co-movement region. Existing literature studying this phenomenon examines the effect of USD volatility on currency co-movements within trade blocs, as trade blocs by nature entail substantial currency exchange. Maintaining a broad scope is advantageous as it enables researchers to select from a larger range of currency pairs, allowing them to focus primarily on those with the strongest dependencies (Wang et al., 2024). However, this approach limits the interpretation of a single currency's dependence structure, as the regular-vine model focuses only on the dynamic co-movements between the currency of interest and the one or two other currencies with which it exhibits the strongest correlation within the selected trade bloc.

This paper is most closely related to Patton (2006) and Wang et al. (2024), who utilize pairwise copula to model dependencies between multivariate networks of currency returns. Patton (2006) finds asymmetric dependence between JPY and German Deutsche Mark (DEM) when USD appreciates. Wang et al. (2024) expands on Patton's methodology by analyzing currency pairs within the Regional Comprehensive Economic Partnership (RCEP) and the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP). Wang et al. (2024) employs a regular-vine copula model to identify the currency pairs with the strongest dependencies and the highest volatility in response to USD strength. The main distinction of this paper is its vantage point. Building on Wang et al. (2024)'s findings that currency co-movement increases with greater trade flow, the scope of our analysis is limited to KRW and the currencies of South Korea's 20 biggest trading partners. By narrowing our analysis to KRW and its major trading partners, we can compare the same currency pairs under different contexts and examine how dependencies shift based on USD movements. Although we use South Korea as a case study, this paper contributes to the broader field of currency network analysis as the same methodology can be applied to analyze any currency's dependence structure as well as providing a useful point of comparison for similar or neighboring economies.

This paper examines the impact of the USD's strength on the interdependence of the KRW and other currencies using canonical vine copula (C-vine) models, adapting the methods of Aas et al. (2009), Dißmann et al. (2013), and Patton (2006).

2 Literature Review

The theoretical framework of this paper is constructed using three factions of literature: the global spillover effects of U.S. economic strategy, the asymmetric dependence between currency returns, and the estimation of time-varying copula parameters.

2.1 Monetary Policy Spillover and Exchange Rate Co-Movement

The standard Mundell-Fleming model stipulates that under the free-floating exchange rate, domestic monetary policy is secure from external influences (Fleming, 1962; Mundell, 1963). Numerous research since have shown deviations from the popular theory, providing statistically significant evidence of U.S. monetary policy spillover effect on international sovereign bond prices. The spillover effect occurs through two primary channels: the ”exchange rate channel,” where changes in the Fed’s policy force foreign central banks to balance between reducing interest rate differentials and minimizing exchange rate volatility, and the ”financial channel,” which affects borrowing costs for foreign central banks directly through the shifts in global investor behavior that influence foreign monetary policy decisions (Gilchrist et al., 2019; Albagli et al., 2019).

Monetary policy (MP) spillover implies that bilateral exchange rates are affected by a third country. Take a three-country international economy. In response to a decrease in the federal funds rate, suppose country B narrows the interest rate differential to maintain its export competitiveness, while country C focuses on domestic objectives. As a result, country C’s currency would appreciate against that of country B, driven by factors unrelated to the pairwise relationship between the two currencies. As such, the varying responses of foreign central banks to external influences, a phenomenon known as monetary policy heterogeneity, generate fluctuations in the bilateral exchange rate between two currencies. Berg and Mark (2015) note that exchange rate factors significantly impact monetary policy in countries like Australia, Indonesia, and Switzerland, while interest rate factors significantly influence policy in countries like Canada, India, and South Korea. These findings altogether contribute to this paper as they reveal the potential for patterns in dynamic currency interdependence that we aim to explore.

2.2 Asymmetric Dependence

Patton (2006) defines asymmetric dependence as a phenomenon where different degrees of correlation between assets are observed under different market conditions. Empirical evidence has consistently shown that correlations between financial assets increase significantly during market downturns due to reduced confidence in the economy (Ang and Chen, 2002; Longin and Solnik, 2001). Assuming symmetry in portfolio construction underestimates the tail risk, creating a negatively biased Value-at-Risk (VaR) (Dißmann et al., 2013).

Patton (2006) extends asymmetric dependence modeling beyond its original context of asset portfolios, demonstrating the presence of asymmetric tail dependencies in exchange rate dynamics. Monetary policy heterogeneity could potentially explain this phenomenon. Research indicates that when the DEM depreciates against the USD, the Bank of Japan often prioritize adjusting interest rates to preserve the price competitiveness of Japanese exports to the U.S. (Patton, 2006). The USD's safe-haven property is another possible cause for this phenomenon. The USD, globally recognized as a safe asset, drastically increases in demand during market downturns and thus appreciates (Kaul and Sapp, 2006; Habib and Stracca, 2012). This flight to safety triggers a liquidity spiral, amplifying appreciatory pressure on the USD and depreciatory pressure on non-U.S. currencies (Serdengeçti et al., 2021; Avdjiev et al., 2019).

This shows how USD fluctuation can affect exchange rate interdependence among non-U.S. currencies, especially during periods of strong USD, as their valuations become increasingly linked through shared exposure to dollar-driven capital flows and risk sentiment shifts (Serdengeçti et al., 2021). Empirical evidence further supports this, showing that as the USD appreciates, deviations from covered interest parity increase, reflecting heightened financial stress and market fragmentation (Avdjiev et al., 2019). Finally, related research finds a statistically significant increase in exchange rate interdependence between currencies in RCEP and CPTPP as USD strengthens, providing a robust background for this paper (Wang et al., 2024).

2.3 Empirical Methods

Sklar's theorem allows for the modeling of multivariate joint distribution using a "cascade of simple building blocks called pair-copulae" (Sklar, 1959; Aas et al., 2009). Vine-copula models expand upon Sklar's theorem by constructing multivariate dependence structures using a hierarchical series of bivariate copulas, while allowing arbitrary univariate marginal distributions (Aas et al., 2009). Deconstruction of multivariate joint distribution into pair-wise marginals allows greater flexibility when the shape of underlying bivariate marginal distributions, known as copula families, is non-normal or differs between pairs (Dißmann et al., 2013).

Vine copula models gained popularity through financial applications, particularly in the context of Value-at-Risk (VaR) analysis as vine copulas are well-suited to capture tail asymmetries that often exist in VaR estimates. (Dißmann et al., 2013). Vine copulas are illustrated using a series of trees. In Tree 1, nodes are the variables and edges show direct relationships between pairs. Each subsequent tree uses the previous tree's edges as nodes, with new edges showing conditional relationships (Aas et al., 2009).

Existing literature, Wang et al. (2024) and Patton (2006), models regular-vine structure as it offers greater flexibility by allowing any pair of variables to be connected at any level (Wang et al., 2024). However, this paper, given its unique vantage point, models exchange interdependence using a canonical-vine structure where one central variable governs the dependencies at each tree level. Popularized by Aas et al. (2009), C-vines are advantageous when one variable is hypothesized to be "[governing the] interactions" in the dataset. As this paper investigates the effect of USD's strength on the exchange rate interdependence between KRW and its main trading partners, two C-vine models are fitted using DSI (Dollar Strength Index) and KRW as their central nodes.

3 Data

First, “Annual import and export status by country” data is obtained from the Korean Statistical Information Service (KOSIS) to identify the 20 biggest trading partners of South Korea.[1] The average sum of annual export and import values is used to determine the 20 biggest trading partners. The following are the top 20 countries with whom Korea had the highest trade flows between 2006 and 2024: United States, China, Japan, Hong Kong, Vietnam, Taiwan, Singapore, India, Germany, Mexico, Türkiye, Indonesia, Australia, Philippines, Malaysia, Russia, United Arab Emirates, Netherlands, Canada, and Qatar.

Our sample consists of the bilateral exchange rates of 16 currencies over the period between January 2006 and August 2024. The data is obtained from the Bank for International Settlements (BIS) database.[2]All exchange rates are presented as monthly averages of indirect quotes, with all exchange rates denominated in U.S. Dollars (USD). From Korea's 20 biggest trading partners identified above, Hong Kong Dollar, United Arab Emirates Dirham, and Qatari Riyal are excluded as they are pegged to the USD. Germany and the Netherlands are combined into one variable as they are both part of the Eurozone. The Turkish Lira is excluded due to the Turkish Lira Crisis during the sampling period. Finally, the USD is excluded as its strength will be regressed independently using the Dollar Strength Index (DSI).

This study utilizes the Nominal Broad Dollar Index (broad DXY), obtained from the Federal Reserve Economic Database (FRED) to measure the strength of USD.[3] While most related literature uses the U.S. Dollar Index (DXY), broad DXY offers a more comprehensive analysis. This index, maintained by the Federal Reserve, incorporates a broader basket

[1]Korean Statistical Information Service. (2024). Import and Export Status by Country [Data set]. Retrieved from https://kosis.kr/eng/

[2]Bank for International Settlements.(2025). Bilateral exchange rates [Data set].Retrieved from https://data.bis.org

[3]Board of Governors of the Federal Reserve System (US), Real Broad Dollar Index [RTWEXBGS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/RTWEXBGS, September 30th, 2024.

of currencies from 26 economies that account for the most bilateral trade with the U.S., compared to the six major currencies used in computing DXY. Furthermore, three of the six basket currencies used in DXY computation - EUR, JPY, and CAD – are included in our regression analysis. To minimize the potential collinearity issues, broad DXY is used in this paper. The conventional threshold, broad DXY > 100 (or DSI > 0), is used to mark periods of USD's strength and weakness.

Following Wang et al. (2024), this paper also normalizes the broad DXY into the Dollar Strength Index (DSI) as $\mathrm{DSI} = \ln(\mathrm{DXY}/100)$. Currency returns are measured using negative log differences as $R_t = -\ln(\mathrm{ER}_t/\mathrm{ER}_{t-1})$. Negative log-difference ensures a positive return when the currency appreciates, as a decreasing indirect exchange rates indicate appreciation. Note that increasing DSI indicates an appreciation of the USD, and since the DSI value is already log-transformed, the log-difference in USD currency return is simply calculated as $R_t = \mathrm{DSI}_t - \mathrm{DSI}_{t-1}$.

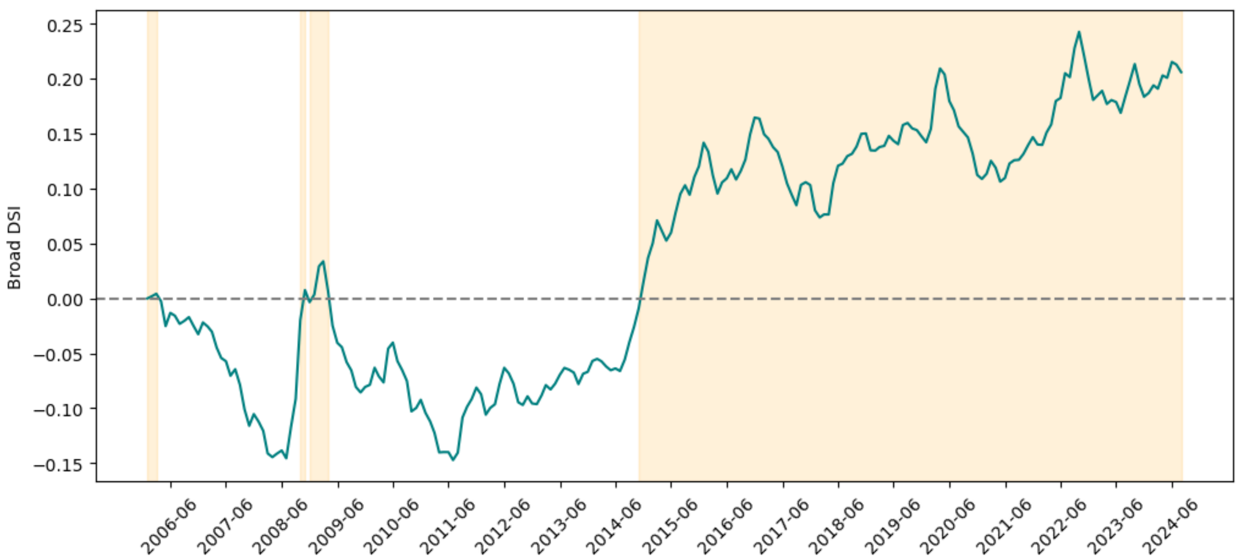
Table 1: Descriptive Statistics of Variables

Currency	Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis	Jarque-Bera	Obs
DSI	0.1026	0.0250	6.7749	-3.1643	1.4047	0.5991	1.6753	39.418 ***	223
AUD	-0.0536	0.1947	7.1063	-17.5350	2.7984	-1.2054	6.3281	426.081 ***	223
CAD	-0.0740	0.0145	6.3800	-10.6461	1.8902	-0.5699	4.2008	176.040 ***	223
CNY	0.0541	0.1544	2.8087	-3.9763	0.9269	-0.9624	3.6117	155.628 ***	223
EUR	-0.0424	-0.0322	6.2130	-7.6752	2.0719	-0.2942	1.0853	14.162 ***	223
INR	-0.2862	-0.0796	4.3981	-6.3692	1.7273	-0.6488	1.7012	42.535 ***	223
IDR	-0.2278	-0.1483	7.2948	-16.4429	2.3051	-1.7217	12.2255	1498.943 ***	223
JPY	-0.1058	-0.1663	7.6261	-7.3987	2.3217	0.0409	1.0619	10.540 ***	223
KRW	-0.1428	-0.0575	8.5677	-15.3668	2.3074	-1.2294	8.8758	788.171 ***	223
MYR	-0.0727	0.0852	5.8200	-6.6335	1.7031	-0.2689	1.3671	20.054 ***	223
MXN	-0.2669	0.1201	8.5672	-17.3356	2.9920	-1.7724	8.5080	789.348 ***	223
PHP	-0.0362	0.0061	3.9728	-4.0109	1.3810	-0.1732	0.4088	2.668	223
RUB	-0.5136	0.0645	28.8880	-28.2412	5.0140	-0.1301	11.1804	1162.093 ***	223
SGD	0.0968	0.2627	3.1259	-3.4796	1.1761	-0.2528	0.0995	2.467	223
TWD	-0.0020	0.0197	3.2910	-3.8740	1.1256	-0.1676	0.6709	5.226 *	223
VND	-0.1885	-0.0388	0.8722	-7.0654	0.6568	-6.7364	59.9531	35084.321 ***	223

Note: Significance at 0.01, 0.05, and 0.1 levels are noted as ***, **, *, respectively. Currency returns are calculated using log differences in exchange rates. Statistics are expressed in percentages. Positive returns indicate appreciation against USD.

Table 1 shows the summary statistics of the currency return series. Overall, all but CNY and SGD exhibit negative average monthly returns. The log-difference of DSI is positive. These combined suggest that the USD has been appreciating overall during our sampling period. This is further supported by Figure 1, which shows broad DXY over our sampling period. Skewness parameters are negative for all currency return series except for JPY, conveying that the underlying currency return distributions tend to be left-skewed. The Jarque-Bera test for normality is statistically significant for most currencies at a 1 percent significance level, indicating a non-normal underlying distribution in the monthly currency return series.

Figure 1: Broad Dollar Index between 2006.01 to 2024.08



Note: The broad Dollar Index is normalized to center around 0. The orange-shaded areas are periods with a strong dollarbroad DXY > 100.

4 Methodology

This paper adopts the methodology of Wang et al. (2024), which follows Dißmann et al. (2013), Patton (2006), and Aas et al. (2009). Modifications to Wang et al. (2024)'s methodology, involving the use of a C-vine rather than an R-vine copula model, are made using the theoretical framework provided in Aas et al. (2009). This paper utilizes Kevin Sheppard's MFE MATLAB GARCH toolbox for marginal estimations, Andrew Patton's MATLAB Copula Toolbox for dynamic estimations, and the 'VineCopulas' package by Claassen et al. (2024) for fitting static C-vine copula models.[4]

According to Sklar's theorem, any multivariate distribution can be written in terms of its marginal distributions and a copula, capturing the individual behaviors and joint behaviors separately. Following Patton (2006), the bivariate CDF of two random variables X, Y can thus be "decomposed" to their marginal CDFs $F_X(x)$, $F_Y(y)$, and its dependence function $C(\cdot)$:

$$F_{XY}(x, y) = C(F_X(x), F_Y(y))$$

Similarly, the bivariate PDF of the same two variables can be expressed in terms of their marginal PDFs $f_X(x)$, $f_Y(y)$, and a copula density function $c(\cdot)$:

$$f_{xy}(x, y) = f_x(x) \cdot f_y(y) \cdot c(F_X(x), F_Y(y))$$

In the context of this paper, the marginal distributions model the individual behavior of each currency's returns, while the copula function captures the dependence structure between the two currency return distributions. For example, if the exchange rates of currency X and currency Y were independent, their joint distribution would simply be $F_{XY}(x, y) = F_X(x) \cdot F_Y(y)$, and the copula function, $C(\cdot)$, would be non-existent. In such cases, the copula is referred to as the independence copula. Therefore, testing for the presence of a copula function will confirm dependence in currency returns, and fitting copula models to our data will allow for the empirical analysis of how the two currency returns move together.

[4] Claassen, J. N., Koks, E. E., de Ruiter, M. C., Ward, P. J., Jäger, W. S. (2024). VineCopulas: an open-source Python package for vine copula modeling. Journal of Open Source Software, 9(101), 6728. https://doi.org/10.21105/joss.06728

4.1 Marginal Estimations of Currency Returns

Following Wang et al. (2024), marginal distributions of currency returns are fitted using the ARMA-GJR-GARCH model. The ARMA-GJR-GARCH estimates the mean and variance for time-series data.

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

The ARMA (autoregressive–moving average) component estimates the time series mean. ARMA(p, q) estimates the auto-regressive parameter (ϕ_i), moving average parameter (θ_j), and the error term (ε_t), based on the time series of observed returns, $\{y_1, y_2, \ldots, y_t = T\}$ (Walker, 1962; Yule, 1927; Patton, 2006).

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I(\epsilon_{t-1} < 0)\epsilon_{t-1}^2$$

The GJR-GARCH component models the time-varying volatility. GJR-GARCH first estimates the conditional variance (σ_t^2) by taking the error term (ε_t) from the ARMA estimation. Then, the auto-regressive parameter (α), the moving average parameter (β), and the asymmetric term (γ), are estimated based on the conditional variance (σ_t^2) and the time series of observed returns $\{y_1, y_2, \ldots, y_t = T\}$ (Engle and Sheppard, 2001; Glosten et al., 1993).

Financial series data often exhibit volatility clustering, asymmetric tails (particularly after negative events), and partial autocorrelation (Glosten et al., 1993; Diebold and Nerlove, 1989; Wang et al., 2024). Given these characteristics, the ARMA-GJR-GARCH model, which effectively captures and isolates these effects, is widely used in relevant studies and will also be conducted for my analysis.

4.2 Canonical Vine Copula

Vine copulas decompose multivariate distributions into pairwise bivariate copulas, constructing hierarchical dependencies by organizing variables in a tree structure. In the context of this paper, Tree 1 consists of nodes that represent the underlying marginal distributions of currency returns. The edges in this tree are bivariate copulas, which measure the dependence between pairs of marginal distributions. Subsequent trees are constructed by transforming the edges of the previous tree into nodes, while the new edges represent conditional dependencies. This structure helps model how the returns of different currencies are related to each other (Aas et al., 2009).

Copula families refer to the different types of copulas used to model dependencies. Following Patton (2006) and Wang et al. (2024), the best-fitting copula families for each currency pair are first determined using the Akaike Information Criterion (AIC)[5] then fitted to construct the vine copulas. Tables 3a, 3b, and 4 present the best-fitting copula families for each currency pair. The Gaussian copula models linear dependence (ρ) between two variables. The t-copula, similar to the Gaussian copula, captures the correlation parameter ρ, but also captures the degrees of freedom parameter ν, making it suitable for distributions with heavier tails. The Frank copula measures symmetric dependence with weak tail dependence, while the Clayton and Gumbel copulas capture asymmetric negative and positive dependence, respectively.[6]

C-Vine, a special type of vine copula, has a star-like structure where all other nodes are connected to a central 'root node.' In this paper, two C-Vine trees are constructed, using DSI and KRW as their respective root nodes. The first C-Vine, with DSI as its root node, is constructed up to the second level.

[5]Lower AIC indicates a better fit.

[6]Refer to the Appendix of Wang et al. (2024) for the specifications and ranges of each copula family

Tree 1, Edge 1 measures unconditional dependence between KRW and DSI:

$$C_{\text{DSI, KRW}} = C(F_{\text{DSI}}(x), F_{\text{KRW}}(y)) \tag{1}$$

Subsequent edges in this tree analogously measure unconditional dependencies between DSI and other currencies.

Tree 2, Edge 1 measures conditional dependence between KRW and AUD, given DSI:

$$C_{\text{KRW, AUD|DSI}} = C_{\text{KRW, AUD}}(F_{\text{KRW}}(x), F_{\text{AUD}}(y) \mid F_{\text{DSI}}(z)) \tag{2}$$

DSI acts as a conditioning variable, isolating its influence on the KRW-AUD relationship. Subsequent edges in this tree would conditionally pair KRW with other currencies while controlling for DSI.

The second C-vine uses KRW as its root node and is only constructed up to the first level. Tree 1, Edge 1 measures unconditional dependence between KRW and AUD:

$$C_{\text{KRW, AUD}} = C(F_{\text{KRW}}(x), F_{\text{AUD}}(y)) \tag{3}$$

Subsequent edges analogously measure unconditional dependencies between KRW and other currencies.

In our model, each currency pairs are fitted using different copula families. While copula parameters are useful for comparisons within the family, they cannot be used to compare across families since each copula family produces parameters on different scales. Therefore, rank-based dependence measure Kendall's Tau τ is used to compare parameters across different families. By comparing τ from specification (1) and (3), this paper examines how USD movements influence both the strength and direction of dependencies between KRW and its trading currencies.

4.3 Dynamic Copula

Dynamic copulas allow the static copula parameter θ to vary over time. Following Patton (2006) and Wang et al. (2024), the dynamic copula parameter θ_t is estimated on a rolling basis using a 12-month window. At each time window, the log-likelihood is computed using functions from Andrew Patton's MATLAB Copula Toolbox. The estimated θ_t values are then modeled using an ARMA(1,1) process.

$$\theta_t = \Lambda\left\{\phi_0 + \phi_1\theta_{t-1} + \phi_2(u_{t-1} - 0.5)(v_{t-1} - 0.5)\right\} \tag{1}$$

$$\theta_t = \Lambda\left\{\phi_0 + \phi_1\theta_{t-1} + \phi_2(u_{t-1} - 0.5)(v_{t-1} - 0.5) + \phi_3\Delta DSI_{t-1}\right\} \tag{2}$$

$$\theta_t = \Lambda\left\{\phi_0 + \phi_1\theta_{t-1} + \phi_2(u_{t-1} - 0.5)(v_{t-1} - 0.5) + \phi_3\Delta DSI_{t-1} + \phi_4\Delta DSI^{asy}_{t-1}\right\} \tag{3}$$

Following Wang et al. (2024), the above regressions are fitted to model how USD appreciation affects the currency co-movements between KRW and its 20 biggest trading partners. Logistic transformation, represented by Λ, ensures that the dynamic copula parameter estimates, θ_t, stay in their domain. ϕ_0, the intercept parameter, indicates the baseline level of dependency between currency returns when other factors are controlled. $\phi_1\theta_{t-1}$, the autoregressive parameter, captures the persistence effect. ϕ_2 captures the interaction effect of the two marginal distributions, where μ_{t-1} and v_{t-1} are shifted marginal distributions of KRW and its trading partners, respectively.

An additional parameter, $\phi_3\Delta DSI_{t-1}$, is added for (2) to capture the effect of DSI changes on currency pair dependencies. Finally, a binary variable $\phi_4\Delta DSI^{asy}_{t-1}$ is introduced in Equation (3) to measure the impact of DSI strength on the interdependence between KRW and its trading currencies. The variable ΔDSI^{asy}_{t-1} is set to 1 when $DSI > 0$ and 0 when $DSI < 0$.

5 Results

Table 2: Marginal Estimations by ARMA-GJR-GARCH model

	DSI	**AUD**	**CAD**	**CNY**	**EUR**	**INR**	**IDR**	**JPY**
Distribution	skewstudent	skewstudent	t	ged	t	skewstudent	ged	ged
μ	-0.090	-0.054	-0.071	0.060	-0.042	-0.286*	-0.225	-0.101
AR.L1	-0.832***	0.158	0.005	0.326***	0.279***	-0.304	-0.417***	1.479***
AR.L2	0.071	-0.189	-0.349*			0.130		-0.796***
MA.L1	1.285***	0.244	0.306	0.224**		0.603	0.732***	-1.277***
MA.L2	0.380***	0.183	0.399*			-0.055		0.638***
ω	0.171	0.311	0.249	0.011	0.310	0.027	0.559	0.125
α	0.000	0.017	0.101	0.144	0.012	0.124	0.053	0.048
β	0.801***	0.856***	0.827***	0.821***	0.838***	0.847***	0.538***	0.900***
γ	0.173	0.165*	-0.018	0.069	0.137	0.057	0.702*	0.064
Skew	-0.383***	-0.389***				-0.172**		
Kurtosis	2.359	5.250	5.016	3.438	1.166	1.477	10.676	0.732
Shape			7.681*	1.010***	10.183*		1.069***	1.460***

	KRW	**MYR**	**MXN**	**PHP**	**SGD**	**TWD**	**RUB**	**VND**
Distribution	skewstudent	t	skewstudent	skewstudent	skewstudent	t	skewstudent	skewstudent
μ	-0.137	-0.062	-0.273	-0.031	0.100	0.021	-0.516	-0.188
AR.L1	0.473***					1.101***	0.342***	0.214***
AR.L2	-0.239***					-0.150	-0.137**	
MA.L1		0.393***	0.287***	0.338***		-0.579		
MA.L2			-0.035			-0.420		
ω	0.236	0.329**	3.510**	0.035	0.257**	0.020	0.815	0.078**
α	0.000	0.125	0.000	0.042	0.000	0.758	0.000	0.758
β	0.827	0.722***	0.374	0.938***	0.706***	0.971***	0.827***	0.178*
γ	0.225	0.055	0.642	0.000	0.160	0.013	0.255*	0.128
Skew	-0.220		-0.153	-0.239*		-0.385***	-0.452***	-0.385***
Kurtosis	5.574	1.664	8.571	0.458	0.582	0.934	24.965	67.531
Shape		9.694*				9.627*		

Note: Significance at 0.01, 0.05, and 0.1 levels are noted as ***, **, *, respectively.

Table 2 shows the marginal distribution parameters fitted using the ARMA-GJR-GARCH model. Most currencies, with the exception of CNY and SGD, exhibit negative mean values, with RUB showing the lowest at -0.516. This indicates that, on average, most currencies depreciated against the USD over the sampling period.

The auto-regressive terms, $AR.L1$ and $AR.L2$, are statistically significant for most currencies. Among them, most exhibit positive $AR.L1$ coefficients[7], indicating that positive returns in the previous periods are likely to be followed by positive returns in the next period and vice versa. In particular, JPY and TWD exhibit the highest $AR.L1$ values, greater than 1. This indicates that JPY and TWD are more likely to persist in their long-term trends. Strong negative $AR.L1$ values for DSI and IDR indicate mean reversion, suggesting that a positive return in one period is likely to be followed by a negative return in the next period and vice versa. The large absolute AR values for most currency returns imply that currency returns are generally heavily autocorrelated.

The $MA.L1$ coefficients show how past shocks affect future returns. DSI and IDR exhibit strong positive persistence, meaning that past shocks whether positive or negative will push the next period returns towards the same direction. JPY shows negative shock persistence, indicating mean reversion. CNY and MYR show mild positive persistence. The $MA.L2$ coefficients for CAD and JPY suggest that shocks from two periods ago still influence returns. Interestingly, JPY has a significant negative shock persistence after one period but positive persistence after two periods. This suggests that JPY over-corrects in its mean reversion tendencies in the short-run, leading to a negative-shock persistence in the medium-run. Overall, these results suggest that shocks affect returns with varying persistence across different currencies.

The ARCH parameters (α) are close to zero for most currencies, indicating that shocks only affect currency returns for a short time. The GARCH parameters (β) are statistically significant for most currencies, suggesting strong volatility clustering. Leverage effects (γ) are significant for AUD and IDR, indicating that these currencies respond more strongly to negative shocks than to positive ones, demonstrating asymmetric dependence.

The analysis of currency patterns reveals strong volatility persistence (high β values) across global currency markets, along with significant asymmetric shock responses (γ parameters) in currencies such as AUD, IDR, and JPY. Our sample exhibits non-normal characteristics, with

[7] CNY, EUR, JPY, KRW, TWD, RUB, and VND.

prevalent skewed distributions and high kurtosis values, suggesting that currency returns exhibit heavy tails and asymmetry.

Table 3a: Static C-Vine Parameters with DSI as its root node (first tree)

Currency Pair	Family	Rotation	Par1	Par2	df	τ
DSI-KRW	frank	0	0.710	-	1	0.078
DSI-VND	gaussian	0	0.619	-	1	0.425
DSI-TWD	frank	0	9.661	-	1	0.656
DSI-SGD	gumbel	0	1.589	-	1	0.371
DSI-RUB	frank	0	3.561	-	1	0.354
DSI-PHP	gaussian	0	0.630	-	1	0.433
DSI-MXN	frank	0	5.990	-	1	0.514
DSI-MYR	frank	0	2.104	-	1	0.224
DSI-JPY	frank	0	4.010	-	1	0.389
DSI-IDR	frank	0	3.886	-	1	0.380
DSI-INR	student	0	0.740	9.502	2	0.530
DSI-EUR	frank	0	3.764	-	1	0.370
DSI-CNY	gaussian	0	0.710	-	1	0.502
DSI-CAD	student	0	0.762	5.002	2	0.552
DSI-AUD	student	0	0.614	8.581	2	0.421

Note: Copula Parameter (Par1); Degrees of Freedom Parameter for Student-t copula indicating heaviness of tails (Par2); Pair-copula Degrees of Freedom (df); Kendall's Tau (τ)

Figure 2: Tree 1 diagram of DSI-centered C-Vine

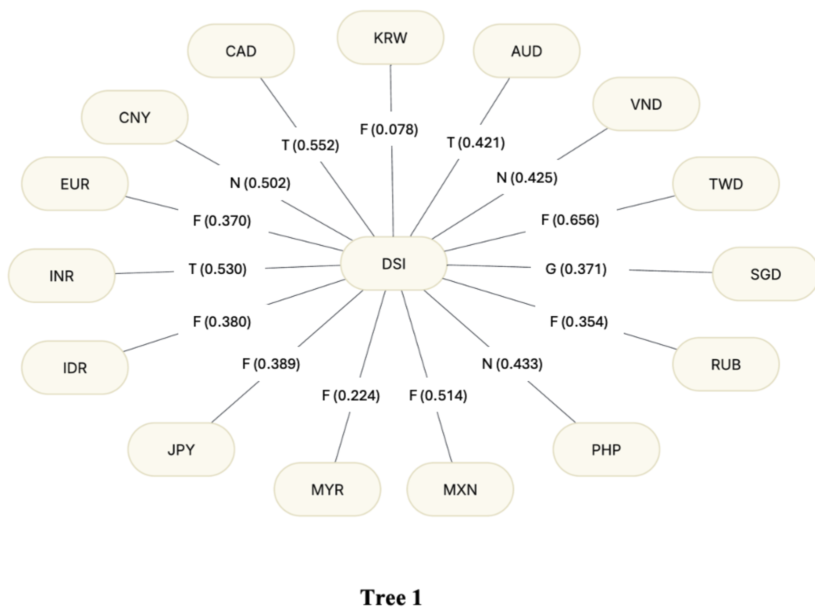
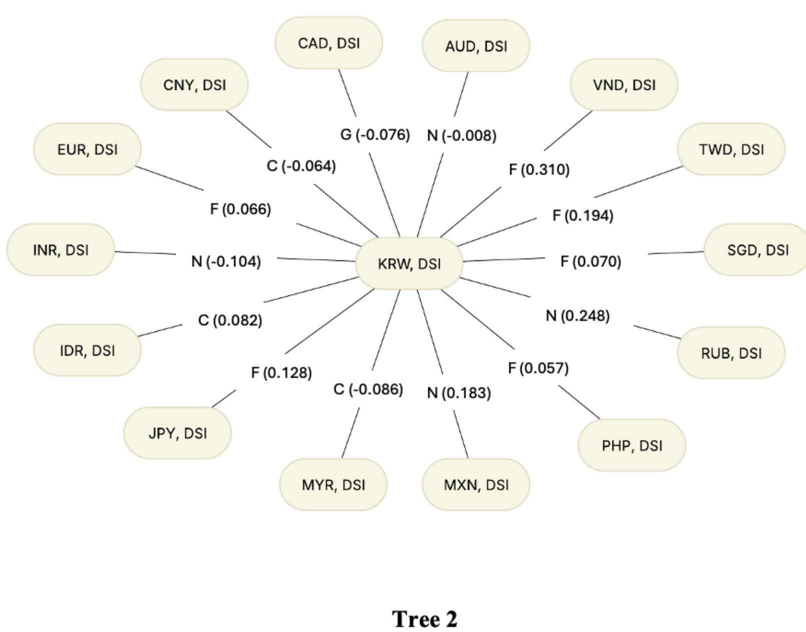


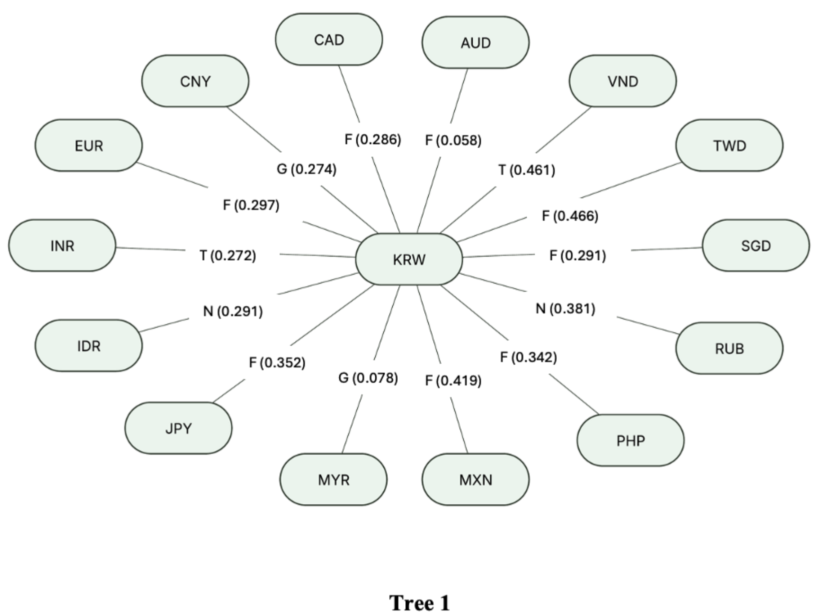
Figure 3: Tree 2 diagram of DSI-centered C-Vine



Note: Significance at 0.01, 0.05, and 0.1 levels are noted as ***, **, *, respectively. Copula Families: N(Normal/Gaussian); T(Student-t); F(Frank); G(Gumbel); C(Clayton). Kendall's Tau coefficients are shown in parentheses.

Figure 2 presents the C-vine results with DSI as the root node in the first tree. When DSI-centered, all currencies in the sample exhibit consistently positive dependencies ($\tau > 0$) with DSI, suggesting that USD appreciation has a unifying effect on currency movements. The prevalence of Frank copulas in this structure indicates that while currencies tend to move together under USD influence, this dependency does not intensify during extreme market events. However, for INR and AUD, the presence of Student-t copulas suggests stronger tail dependencies, meaning these currencies exhibit greater co-movements with USD during market extremes.

Figure 4: Tree diagram of KRW-centered C-Vine



Note: see the footnote in Figure 3

Table 3b: Static C-Vine Parameters with KRW as its root node (second tree)

Currency Pair	Conditioning Variable	Copula Family	Rotation	Par1	Par2	df	τ
KRW-AUD	DSI	gaussian	0	-0.012	-	1	-0.008
KRW-VND	DSI	frank	0	3.027	-	1	0.310
KRW-TWD	DSI	frank	0	1.800	-	1	0.194
KRW-SGD	DSI	frank	0	0.630	-	1	0.070
KRW-RUB	DSI	gaussian	0	0.380	-	1	0.248
KRW-PHP	DSI	frank	0	0.511	-	1	0.057
KRW-MXN	DSI	gaussian	0	0.284	-	1	0.183
KRW-MYR	DSI	clayton	90	0.188	-	1	-0.086
KRW-JPY	DSI	frank	0	1.166	-	1	0.128
KRW-IDR	DSI	clayton	0	0.180	-	1	0.082
KRW-INR	DSI	gaussian	0	-0.163	-	1	-0.104
KRW-EUR	DSI	frank	0	0.600	-	1	0.066
KRW-CNY	DSI	clayton	90	0.136	-	1	-0.064
KRW-CAD	DSI	gumbel	270	1.082	-	1	-0.076

Note: see the footnote in Table 3a

Table 4: Static C-Vine Parameters with KRW as its root node (first tree)

Currency Pair	Copula Family	Rotation	Par1	Par2	df	τ
KRW-AUD	frank	0	0.525	-	1	0.058
KRW-VND	student	0	0.663	9.206	2	0.461
KRW-TWD	frank	0	5.148	-	1	0.466
KRW-SGD	frank	0	2.811	-	1	0.291
KRW-RUB	gaussian	0	0.564	-	1	0.381
KRW-PHP	frank	0	3.412	-	1	0.342
KRW-MXN	frank	0	4.427	-	1	0.419
KRW-MYR	gumbel	180	1.085	-	1	0.078
KRW-JPY	frank	0	3.528	-	1	0.352
KRW-IDR	gaussian	0	0.441	-	1	0.291
KRW-INR	student	0	0.414	9.123	2	0.272
KRW-EUR	frank	0	2.881	-	1	0.297
KRW-CNY	gumbel	180	1.377	-	1	0.274
KRW-CAD	frank	0	2.759	-	1	0.286

Note: see the footnote in Table 3a

Figure 4 shows the unconditional dependencies between KRW and all other currencies. Like Figure 2, all dependencies are positive but are generally weaker, with τ values ranging from 0.461 (KRW-VND) to 0.058 (KRW-AUD). This suggests that currencies in the sample, despite being KRW's biggest trading partners, are more closely correlated with USD than with KRW, which is consistent, given the broader role of USD in global financial markets.

Figure 3 examines the co-movements between KRW and other currencies, conditioned on DSI. A comparison of Tables 3b and 4 reveals the USD's directional influence on KRW-currency pairs. After controlling for USD effects, all positive dependencies weaken, as shown by significantly lower τ values in Table 3b. Additionally, dependencies for KRW-AUD, KRW-INR, KRW-CAD, and KRW-MYR shift from positive to negative when conditioned on DSI, suggesting that USD appreciation can mask or even reverse the intrinsic relationships between these currency pairs. This implies that USD strength artificially aligns currencies that might otherwise move in opposite directions. The change in copula families in Table 3b further indicates changes in dependency structures when USD effects are removed. For instance, the emergence of Clayton copulas for KRW-MYR and KRW-IDR suggests asymmetric dependencies that were not apparent when USD dominated the structure.

Overall, the static C-vine estimations suggest that USD appreciation causes KRW and its trading partners' currencies to move more similarly, inflating correlation estimates. Moreover, DSI volatility appears to obscure the true dependencies between currency pairs. When USD effects are filtered out, many dependencies weaken or reverse, revealing that the intrinsic relationships between currencies differ substantially from what is observed under USD influence.

Table 5: Dynamic Estimates of Copula Parameters

Currency Pair	Copula Family	ϕ_0	ϕ_1	ϕ_2
KRW-AUD	frank	-3.092***	6.004***	-0.005
KRW-VND	student	-1.780*	3.632**	-0.003
KRW-TWD	frank	-5.070***	10.217	0.018
KRW-SGD	frank	-4.661***	7.014***	0.030
KRW-RUB	gaussian	-2.013**	4.084***	0.001
KRW-PHP	frank	-5.271***	40.329	0.006
KRW-MXN	frank	-3.665***	5.890***	-0.032
KRW-MYR	gumbel	-2.518***	5.491*	0.001
KRW-JPY	frank	-2.278***	4.623***	-0.039
KRW-IDR	gaussian	-1.669**	3.570***	0.000
KRW-INR	student	-1.950	3.931*	0.000
KRW-EUR	frank	-3.072***	5.426***	-0.058
KRW-CNY	gumbel	-2.246***	4.607*	-0.000
KRW-CAD	frank	-2.832***	4.276***	0.004

Note: Significance at 0.01, 0.05, and 0.1 levels are noted as ***, **, *, respectively. Intercept Coefficient (ϕ_0); Autoregressive Component (ϕ_1) ; Variation Effect(ϕ_2);

Table 6: Dynamic Estimates of Copula Parameters with direct USD Effect ($\Delta \mathrm{DSI}_{t-1}$)

Currency Pair	Copula Family	ϕ_0	ϕ_1	ϕ_2	ΔDSI$_{t-1}$
KRW-AUD	frank	-3.092***	5.942***	-0.011	15.470
KRW-VND	student	-1.751*	3.574**	0.012	-2.503
KRW-TWD	frank	-5.092***	10.198	0.031	-8.939
KRW-SGD	frank	-4.683***	7.020***	-0.014	34.381
KRW-RUB	gaussian	-2.016**	4.088***	0.000	0.363
KRW-PHP	frank	-5.265***	40.302	0.000	5.023
KRW-MXN	frank	-3.660***	5.792***	-0.054	25.731
KRW-MYR	gumbel	-2.509***	5.460*	-0.000	1.024
KRW-JPY	frank	-2.290***	4.665***	-0.036	-13.909
KRW-IDR	gaussian	-1.664**	3.562***	0.000	-0.522
KRW-INR	student	-1.950	3.930*	0.000	-0.055
KRW-EUR	frank	-3.066***	5.326***	-0.075	18.127
KRW-CNY	gumbel	-2.249***	4.616*	0.000	-0.187
KRW-CAD	frank	-2.877***	4.226***	-0.008	27.101

Note: See the footnote in Table 5

Table 7: Dynamic Estimates of Copula Parameters with USD Strength Effect ($\Delta\text{DSI}^{\text{asy}}_{t-1}$)

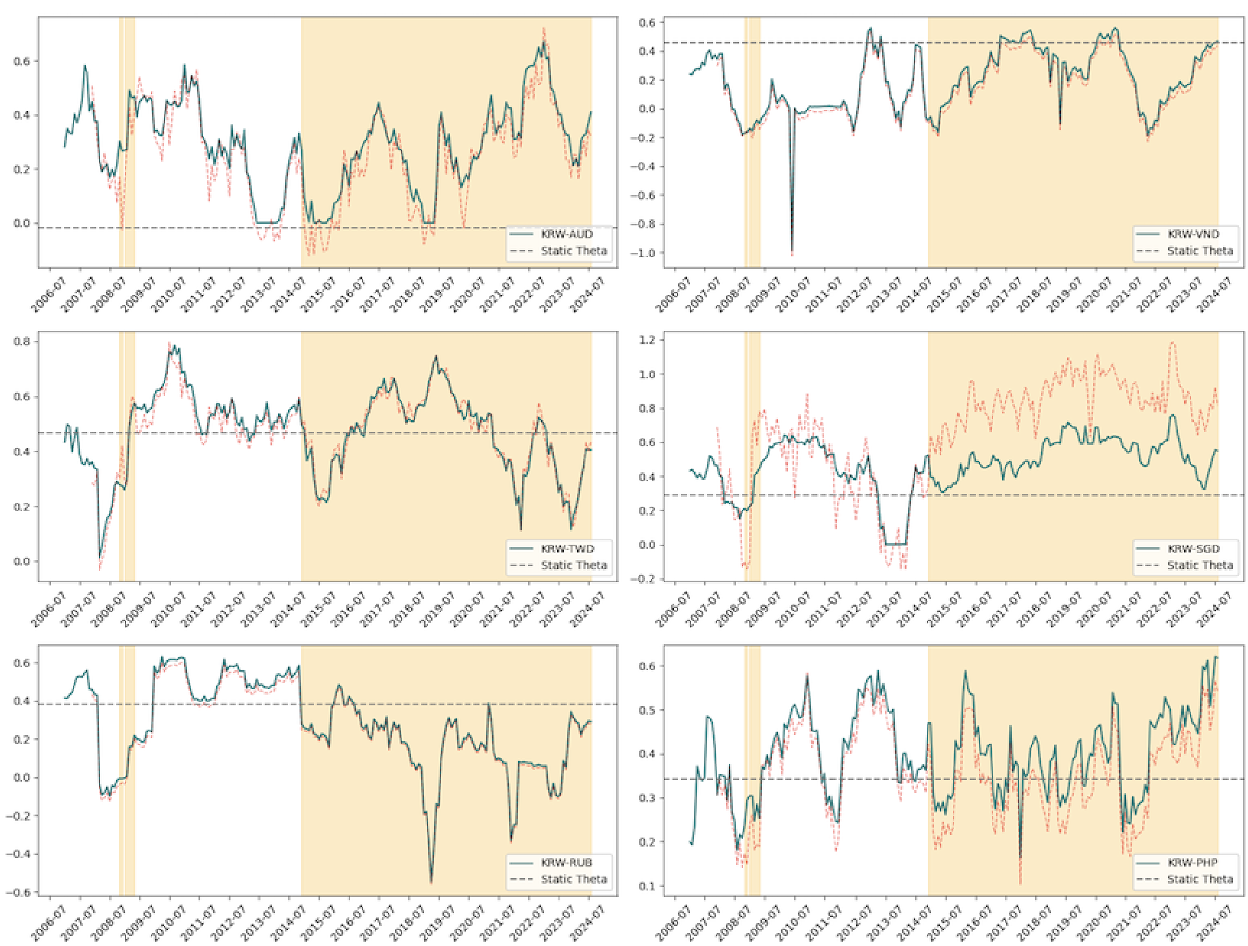
Currency Pair	**Copula Family**	ϕ_0	ϕ_1	ϕ_2	**Δ**DSI$_{\text{t-1}}$	**Δ**DSI$_{\text{t-1}}$asy
KRW-AUD	frank	-3.118***	5.940***	-0.010	15.212	0.044
KRW-VND	student	-1.723	3.475*	0.012	-2.807	0.050
KRW-TWD	frank	-5.024***	10.024	0.030	-8.586	-0.116
KRW-SGD	frank	-3.894***	6.206***	-0.043	49.082	-2.070
KRW-RUB	gaussian	-1.877*	3.939***	0.000	0.499	-0.072
KRW-PHP	frank	-5.335***	40.522	0.001	5.094	0.110
KRW-MXN	frank	-4.959***	5.273***	-0.058	20.942	1.796
KRW-MYR	gumbel	-2.516***	5.411*	-0.000	0.964	0.029
KRW-JPY	frank	-1.425***	4.195***	-0.030	-7.650	-1.158**
KRW-IDR	gaussian	-1.677**	3.550***	0.000	-0.646	0.038
KRW-INR	student	-1.932	3.909	0.000	-0.004	-0.009
KRW-EUR	frank	-3.007***	5.318***	-0.075	19.083	-0.097
KRW-CNY	gumbel	-2.224**	4.577*	0.001	-0.174	-0.026
KRW-CAD	frank	-3.026***	4.206***	-0.007	25.730	0.248

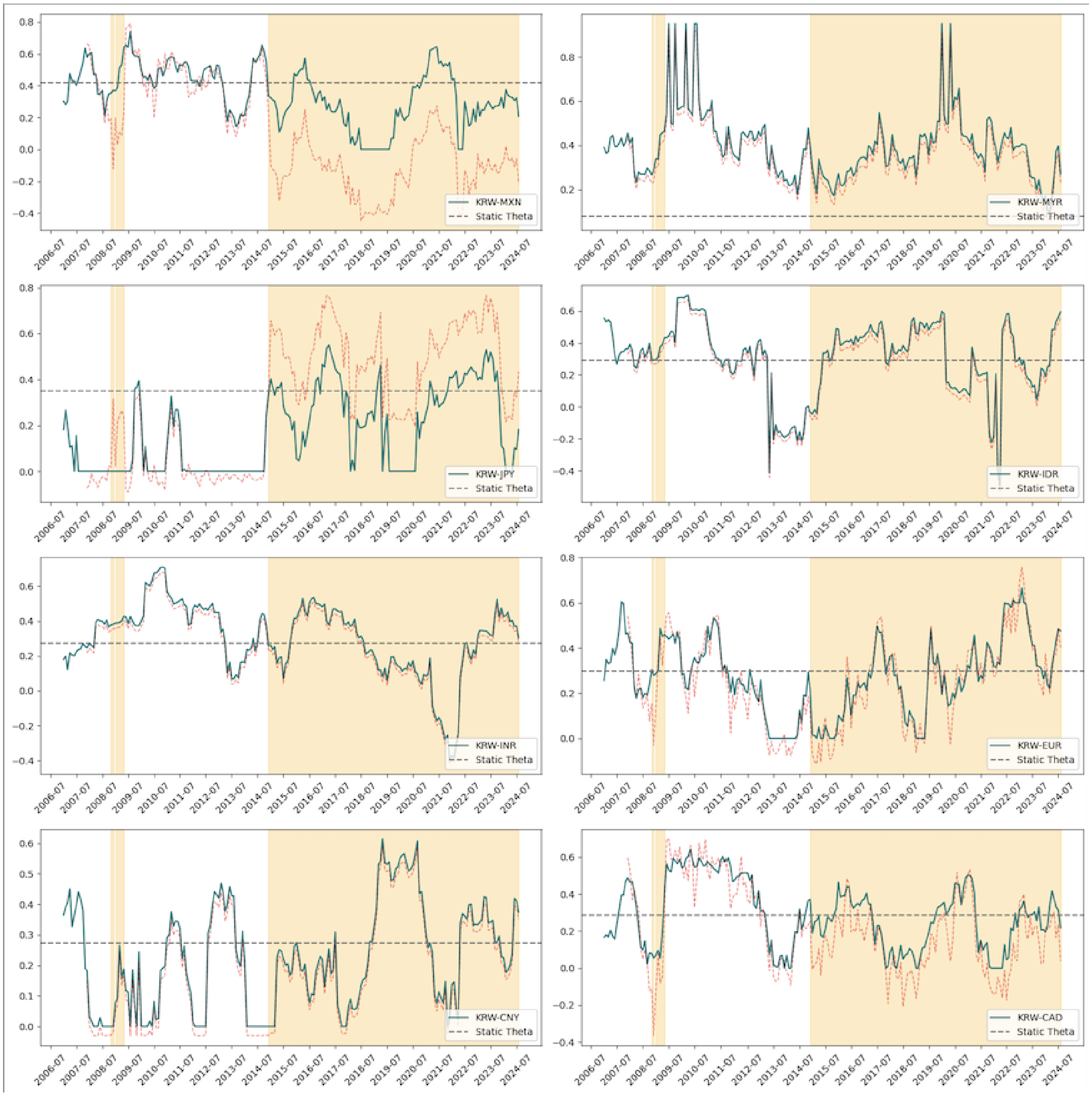
Note: See the footnote in Table 5

As shown in tables 5, 6, and 7, ϕ_0 and ϕ_1 parameters remain relatively consistent and statistically significant across all three regression models, suggesting robustness in the base dependency structure. Consistently negative ϕ_0, ranging from -1.425 (KRW-JPY) to -5.335 (KRW-PHP), indicates that there is a baseline level of negative dependency when other factors are accounted for. Autoregressive parameters ϕ_1 are consistently positive and statistically significant across all currency pairs, demonstrating a strong persistence effect in dependency structures over time. The interaction effect is minimal in determining currency interdependence within our sample, suggested by the generally small ϕ_2 estimates.

Although many of the individual ϕ_3 and ϕ_4 coefficients are statistically insignificant, observing the overall pattern provides insights into the directional influence of the USD on currency dependencies. The positive direct USD effect (ΔDSI_{t-1}) shows that a strengthening USD generally increases dependencies between the KRW and most other currencies. The asymmetric USD effects (ΔDSI^{asy}_{t-1}) are mostly positive, indicating that a strong dollar (DSI > 0) also generally increases the currency interdependencies in our sample. However, this trend is not universal across all currency pairs. Negative asymmetric effects are observed between the KRW and TWD, SGD, EUR, CNY, and JPY. For all these currency pairs but KRW-RUB, both the direct USD effect and the asymmetric effect are negative, suggesting a consistent pattern of reduced interdependence with KRW as the Dollar strengthens, regardless of whether it crosses the threshold. The Russian Ruble (RUB) is an exception to this phenomenon. While it shows a positive direct USD effect, its asymmetric effect is negative. This divergence could potentially be due to the prolonged strength of the USD since 2015 and the subsequent depreciation of RUB.

Figure 5: The Dynamic Dependence between KRW and its trading partners





Note: The blue line represents Kendall's Tau estimates (τ) calculated using a 12-month rolling window. The red line represents Kendall's Tau estimates without USD effects. The orange-shaded areas are periods with a strong dollarbroad DXY > 100. The grey line indicates the static C-vine parameter of each currency pair.

Figure 5 presents the time-varying Kendall's Tau coefficient (τ) between KRW and its trading partners over the sampling period. The blue line represents the dynamically estimated Kendall's Tau, using Equation 3. The red line represents the dynamic dependence without the USD effects. This is computed by setting ϕ_3 and ϕ_4 in equation 3 to 0. The orange-shaded area represents periods of Dollar strength ($DXY > 0$).

The USD effects generally increase the currency interdependence between KRW and its trading partners, as evidenced by the red line (without USD effects) typically appearing below the blue line (with USD effects). This finding aligns with our static C-vine results and the findings of Mai et al. (2018) that USD serves as a central connecting factor in the global currency network, amplifying the interdependence between non-US currencies. Furthermore, we observe a significant increase in currency interdependence across most pairs during a brief period of dollar strength between late 2008 and early 2009, attributable to the global financial crisis. This pattern favors the safe-haven hypothesis of currency interdependence.

Since 2015, the dollar has maintained a relatively strong position, allowing for the examination of the persistent dollar strength effect on pairwise currency relationships. Although the persistent dollar strength effect is minimal for most currencies, a few currencies show a distinct divergence in dynamic interdependencies when the USD effects are removed during dollar strength. The MXN and CAD show lower dependencies with KRW when USD effects are removed, with this divergence being particularly amplified during periods of dollar strength. In contrast, the JPY and SGD show higher dependencies with KRW when USD effects are removed, with this phenomenon significantly amplified during periods of dollar strength. Similarly, though to a lesser extent, the Taiwanese Dollar (TWD) shows elevated dependencies with KRW when the influence of the USD is eliminated.

The direction of the persistent dollar strength effect is not uniform across KRW-centered currency pairs. Economic integration may explain this variation. Japan, Taiwan, and Singapore are economically similar to South Korea through integrated supply chains and collaborative industries. This regional interconnectedness might lead to stronger currency dependencies when the influence of the USD is reduced or during periods of dollar appreciation, as these economies may engage in more direct currency exchanges. In contrast, Mexico and

Canada are economically more similar to the U.S., which could result in their trade with South Korea being predominantly USD-denominated. This difference in regional integration could explain how different currencies respond to persistent dollar strength. Those with stronger regional connections to South Korea may exhibit more robust dependencies with KRW during dollar strength periods, while currencies more closely linked to the US might show weaker direct relationships with KRW when USD effects are removed.

6 Conclusion

This study investigates how dollar strength influences currency interdependence between South Korea and its trading partners. Our univariate analysis reveals that most currency returns exhibit strong autocorrelation and cluster during periods of high volatility but vary in the extent of their trend persistence, consistent with previous studies (Wang et al., 2024). The static C-vine estimations suggest that USD appreciation causes KRW and its trading partners' currencies to move more similarly, inflating correlation estimates. We also find evidence of asymmetric dependence, as USD depreciation does not weaken dependencies among KRW-centered currency pairs to the same extent as USD appreciation. However, DSI volatility also appears to obscure the true dependencies between currency pairs, as when USD movements are controlled, many dependencies weaken or reverse, revealing that the true bilateral relationships between currencies are different from what is observed under USD influence. Thus, we find that the observed correlations between KRW and its trading partners' currencies are significantly shaped by the overarching influence of the USD, and not necessarily by direct, independent relationships.

Our dynamic estimations further supports this phenomenon, as evidenced by predominantly positive ϕ_3 and ϕ_4 parameters. The time-varying Kendall's Tau estimates indicate that removing USD effects generally lowers currency dependencies, reinforcing the existing notion that USD acts as a central connecting factor in the global currency network. This pattern aligns with both our static C-vine results and previous literature.

During the 2008–2009 financial crisis, we observe that the rapid appreciation of the USD led to increased interdependence between currencies. This finding favors the safe-haven hypothesis. However, the long-term effects of prolonged dollar strength varies across different currency pairs. Currencies from economies more integrated with South Korea (JPY, SGD, and TWD) show stronger dependencies with KRW, when USD effects are removed. However, currencies of economies that are geographically closer to the U.S. (MXN, CAD) exhibit weaker dependencies, when USD effects are removed. This suggests that regional economic integration plays a crucial role in shaping currency relationships beyond USD-influence. Previous studies report evidence of the USD increasing currency interdependencies. However, this paper uniquely finds that the direction of this effect isn't universal. We identify cases where prolonged USD strength decreases interdependence, an insight made possible by focusing on a single currency rather than the whole regional network.

Overall, the paper provides practical implications for managing risks during periods of prolonged dollar strength and global financial instability. Our findings suggest that central banks could benefit from diversifying their foreign exchange reserves beyond the USD. By analyzing an economy's independent pairwise currency relationships, governments and import-reliant firms can potentially reduce their exposure to the increased cost of production during strong dollar periods. As such, this study can help policymakers and central banks of small open economies understand how the strength of the USD affects their currency exposures, allowing them to manage exchange rate volatility and reduce risks.

Future research implementing this method should consider using higher frequency data. This research uses monthly average exchange rates, which veils substantial intra-monthly volatility. As exchange rates are highly volatile in the short term, it would be beneficial to capture daily fluctuations as it may better depict surprise effects on short-term risk sentiments.

In addition to the given framework, future research could explore how regional economic integration influences currency interdependencies, with a focus on determining the specific factors that affect the direction of the USD strength effect. This could involve incorporating additional variables such as economic integration measures, export reliance levels, monetary policy changes, and trade balances between currency pairs into the regression model. The same methodology could be adapted to examine the impact of other emerging 'key' currencies or safe-haven currencies, like the CNY and JPY, on regional currency interdependence. Additionally, given the exclusion of most oil-exporting countries from this study due to their currencies being pegged to the USD, it would be valuable to analyze how oil prices affect relationships between the KRW and currencies of oil-exporting nations. Such research could provide insights about future commodity prices, exchange rates, and economic ties in different regions, ultimately helping to develop strategies for managing currency risks and maintaining financial stability in the increasingly interdependent economy.

7 Appendix

Table 9: Currency Codes and Their Full Names

Currency Code	**Currency**
USD	United States Dollar
KRW	South Korean Won
AUD	Australian Dollar
CAD	Canadian Dollar
CNY	Chinese Yuan
EUR	Euro
INR	Indian Rupee
IDR	Indonesian Rupiah
JPY	Japanese Yen
MYR	Malaysian Ringgit
MXN	Mexican Peso
PHP	Philippine Peso
RUB	Russian Ruble
SGD	Singapore Dollar
TWD	New Taiwan Dollar
VND	Vietnamese Dong

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