

Epicenter or bystander? Currency connectedness around the 2024 yen carry unwind

Hongquan Li

Hunan Normal University

Zhenting Gong

k1ausegong@hunnu.edu.cn

Hunan Normal University

Article

Keywords:

Posted Date: October 29th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10660580/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Epicenter or bystander? Currency connectedness around the 2024 yen carry unwind

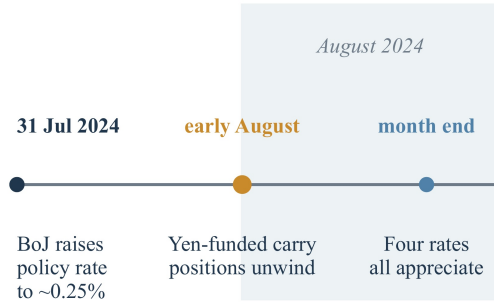
Abstract. When a carry-trade funding currency appreciates, investors may unwind positions in several currencies at the same time, reducing diversification within the portfolio. The August 2024 yen carry unwind raised a practical question about which positions are most exposed when currencies move together. We estimate Diebold–Yilmaz and a multi-period Genizi R^2 connectedness measure from the same time-varying forecast system for monthly dollar returns on EUR, GBP, JPY, and CHF from February 1975 to January 2026. Connectedness rises sharply around funding stress. Over the full sample, both measures identify GBP and JPY as net receivers—the currencies most affected by the rest of the portfolio. The August 2024 episode shows the same pattern, with both GBP and JPY exposed to the unwind even though the measures disagree on which is more affected. The visible jump in JPY therefore does not show that connectedness was concentrated in JPY. For investors, GBP and JPY should be considered together when the funding currency moves sharply.

Keywords: foreign exchange markets; dynamic connectedness; TVP-VAR; R^2 connectedness; carry trade

1 Introduction

The risk in a carry trade becomes acute when the funding currency appreciates, because losses on the funding leg arrive just as leveraged investors unwind their positions (Brunnermeier et al., 2008). August 2024 made this vulnerability concrete. After the Bank of Japan raised its policy rate to around 0.25 percent on 31 July, market volatility rose and yen-funded positions were unwound (Bank of Japan, 2024; Aquilina et al., 2024). JPY appreciated by 7.46 percent against the U.S. dollar during August, its eighth largest monthly gain in our five-decade sample. The adjustment also extended beyond the funding currency, as CHF, EUR, and GBP strengthened against the dollar (Figure 1).

A. The episode



B. August appreciation against USD

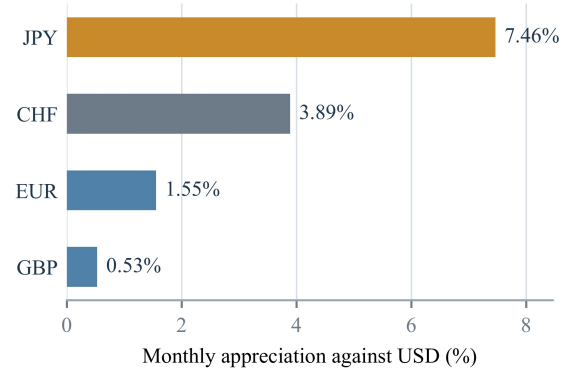


Figure 1. The August 2024 yen carry unwind. Panel A records the Bank of Japan policy change and the subsequent unwind of yen-funded positions. Panel B reports the appreciation of each currency against the U.S. dollar in August 2024. The appreciation values are the sign-reversed monthly returns used to estimate connectedness.

For a currency investor, the episode raised a question that returns alone cannot answer. Common movement across positions indicates that diversification has weakened, but it does not show whether the dependence is concentrated in the funding currency, a position held for protection, or a particular currency pair. The distinction matters for portfolio management: a broad increase in dependence changes the risk of the portfolio as a whole, whereas concentration in one currency or pair changes the assessment of particular positions and hedges. Connectedness analysis measures both system-wide dependence and its distribution across currencies and pairs.

This portfolio problem follows from two established features of currency markets. Currency portfolios reveal common priced risk, and innovations in global foreign-exchange volatility help explain differences in their average returns (Lustig et al., 2011; Menkhoff et al., 2012; Lettau et al., 2014). Bilateral exchange rates against the U.S. dollar also contain substantial systematic variation, but individual currencies differ in their exposure to the common factors (Verdelhan, 2018). These differences matter for hedging, because the appropriate currency exposure depends on the covariance between the currency and the underlying foreign asset (Campbell et al., 2010). They are also visible during stress, when JPY and CHF may provide protection but do not perform identically across episodes (Ranaldo and Söderlind, 2010; Habib and Stracca, 2012). Common risk determines how much diversification remains available; heterogeneous exposure determines where the

resulting portfolio risk is concentrated.

Portfolio rebalancing connects these features to the August 2024 episode. Changes in relative asset performance lead investors to adjust domestic and foreign positions, while the exchange-rate response depends on the capacity of intermediaries to absorb the resulting currency demand (Hau and Rey, 2006; Camanho et al., 2022; Gabaix and Maggiori, 2015). Funding pressure can intensify this adjustment by limiting the ability of investors and banks to maintain cross-currency positions (Bruno and Shin, 2017; Avdjiev et al., 2019), so dependence can rise across the portfolio even though the largest imbalance remains concentrated in one currency or pair.

Connectedness methods bring system-wide, currency-level, and bilateral relations into one forecast system (Diebold and Yilmaz, 2014; Greenwood-Nimmo et al., 2016). The total connectedness index (TCI) measures dependence across the system, net total directional connectedness (NET) distinguishes currencies that contribute more connectedness than they receive, and pairwise estimates show where the largest directional imbalances occur. The allocation is not unique when forecast innovations are correlated. Generalized forecast-error variance decompositions assign contributions to individual innovations, whereas Genizi’s decomposition allocates the variation jointly explained by correlated sources (Lastrapes and Wiesen, 2021; Genizi, 1993). The two approaches may therefore produce similar total connectedness while locating that dependence in different currencies and pairs.

We study monthly dollar returns on EUR, GBP, JPY, and CHF from February 1975 to January 2026. Diebold–Yilmaz (DY) and multi-period Genizi R^2 connectedness are calculated from the same time-varying parameter vector autoregression (TVP-VAR), so the currencies, information set, forecast horizon, and estimated parameter paths are identical. The empirical differences therefore come from the way correlated forecast variation is assigned within the system. Monte Carlo experiments evaluate the recursive R^2 estimator under stable, gradually changing, and reversing dependence, and the empirical results are confirmed across alternative estimators, specifications, and sample periods.

At the system level, DY and R^2 connectedness move closely together. The two TCIs

have a correlation of 0.918, although the R^2 estimate is 9.92 percentage points higher on average. The currency and bilateral estimates are less alike. Around the August 2024 unwind, DY identifies JPY as having the lowest NET, whereas R^2 identifies GBP. Both measures nevertheless place GBP and JPY below EUR and CHF in the NET ordering. Over the full sample, the two currencies remain at the lower end of the NET ordering, but EUR–GBP has the largest average absolute NPDC under DY and JPY–CHF under R^2 . Comparisons with earlier episodes show that the size of the TCI difference does not indicate whether the same currencies and pairs account for it.

The paper makes three contributions. First, it introduces TVP-VAR- R^2 connectedness by applying the Genizi decomposition to the multi-period forecast-error correlation matrix generated by a TVP-VAR. Existing R^2 connectedness research develops contemporaneous and lagged allocations, whereas the proposed construction measures jointly explained forecast-error variation at a chosen horizon and yields additive currency-level and bilateral contributions. Second, the paper estimates DY and R^2 networks from the same evolving forecast system, so the currencies, information set, forecast horizon, and parameter paths are identical; their differences can therefore arise only from how correlated forecast variation is assigned, isolating the role of the decomposition itself. Third, total connectedness follows similar paths under the two allocations, whereas currency-level and bilateral estimates are more sensitive to the allocation of correlated forecast-error variation.

2 Literature Review

Evidence on currency risk combines a common component with heterogeneous currency exposures. Returns on interest-rate-sorted currency portfolios covary with common currency and global foreign-exchange volatility factors (Lustig and Verdelhan, 2007; Lustig et al., 2011; Menkhoff et al., 2012; Lettau et al., 2014), while bilateral exchange rates against the U.S. dollar have a compact factor structure with unequal currency exposures (Verdelhan, 2018). This heterogeneity matters for hedging because optimal currency po-

sitions depend on their covariance with the underlying foreign assets (Campbell et al., 2010), and because exchange-rate dependence varies with market conditions and can be asymmetric between joint appreciations and depreciations against the dollar (Bekaert, 1996; Patton, 2006). JPY and CHF can likewise provide protection during stress without performing identically across episodes (Ranaldo and Söderlind, 2010; Habib and Stracca, 2012; De Bock and de Carvalho Filho, 2015; Grisse and Nitschka, 2015; Sato et al., 2024). These findings explain why a loss of diversification need not be concentrated in one currency, but they do not show how the dependence is distributed within a forecast network.

Portfolio adjustment provides an economic channel for this distribution. Order flow conveys information into exchange rates, and changes in relative equity performance induce investors to rebalance between domestic and foreign assets (Evans and Lyons, 2002; Froot and Ramadorai, 2005; Hau and Rey, 2006; Camanho et al., 2022). The response of each currency depends on the exposure being adjusted and on the capacity of intermediaries to absorb the resulting demand (Gabaix and Maggiori, 2015; Maggiori, 2017). Carry-trade stress intensifies this process: returns are exposed to global foreign-exchange volatility, crash risk, and appreciation of the funding currency (Menkhoff et al., 2012; Brunnermeier et al., 2008; Jurek, 2014; Farhi and Gabaix, 2016), while dollar borrowing, bank leverage, and deviations from covered interest parity constrain cross-currency positions (Bruno and Shin, 2017; Du et al., 2018; Avdjiev et al., 2019). Foreign-exchange liquidity also has a strong common component whose sensitivity to funding stress differs across currencies (Mancini et al., 2013; Karnaukh et al., 2015). During the global financial crisis, these pressures coincided as investors and dealers reduced positions (Melvin and Taylor, 2009). They can therefore raise dependence across a currency portfolio while leaving uneven net exposures across funding, investment, and defensive positions.

The distribution of that dependence also changes over time. Volatility innovations pass across international trading centres, and high-frequency exchange-rate volatility varies markedly within and across trading days (Engle et al., 1990; Andersen et al., 2001). Multivariate studies find stronger return and volatility spillovers during adverse

market states and crisis periods (Bubák et al., 2011; Baruník et al., 2017; Rigana et al., 2023). Event-based evidence likewise shows that identifiable global developments alter both the strength and direction of foreign-exchange relations (Albrecht and Kočenda, 2025). Studies using different regional samples and observation frequencies show that the currencies contributing most to a network, and the bilateral relations carrying its largest imbalances, are not fixed over time (Albrecht and Kočenda, 2024; Rubaszek et al., 2025; Zhu et al., 2024; Greenwood-Nimmo et al., 2025).

Connectedness analysis measures this changing dependence within a multivariate forecast system. The Diebold–Yilmaz framework uses forecast-error variance decompositions to construct total and directional spillover measures (Diebold and Yilmaz, 2009, 2012). Its network representation also yields net positions and bilateral directions (Diebold and Yilmaz, 2014). The total connectedness index records the share of forecast uncertainty associated with cross-variable innovations. Directional measures separate the connectedness received by a currency from the connectedness it contributes, while net pairwise measures compare the two directions within a currency pair. These quantities describe different features of the same forecast system rather than competing definitions of a single statistic.

Later connectedness research extends this framework to large systems, frequency decompositions, time-varying parameters, and different parts of the conditional distribution (Demirer et al., 2018; Baruník and Křehlík, 2018; Antonakakis et al., 2020; Ando et al., 2022). Foreign-exchange applications use the resulting networks to study changes in aggregate spillovers, the currencies that contribute or receive them, and the bilateral relations through which they occur (Greenwood-Nimmo et al., 2016, 2025). This literature establishes the value of moving from a system-wide measure to currency and pairwise estimates. It leaves open how stable those estimates are when correlated forecast variation is decomposed in different ways.

Generalized forecast-error variance decompositions evaluate each innovation without imposing a recursive ordering and then normalise the resulting shares by target equation (Koop et al., 1996; Pesaran and Shin, 1998; Diebold and Yilmaz, 2012). This approach is

well suited to directional connectedness, but the contribution attached to one innovation is evaluated in a system in which the innovations are correlated. Lastrapes and Wiesen instead begin with the forecast variation explained jointly by the remaining variables. They show that this joint contribution need not equal the sum of contributions assigned to the same variables individually (Lastrapes and Wiesen, 2021).

Correlated innovations are especially likely in currency markets, where common factors, portfolio rebalancing, and shared funding conditions all operate. How those correlations are treated can affect both the level of measured dependence and its distribution, and the effects need not be proportional across total, net, and pairwise measures. Genizi’s decomposition provides an additive allocation of a multiple coefficient of determination among correlated predictors (Genizi, 1993), an alternative to assigning variation to each source separately. Recent connectedness research uses this allocation to construct contemporaneous and lagged R^2 networks (Gabauer et al., 2023; Balli et al., 2023), making it possible to recover directional and bilateral contributions from joint explanatory variation. Whether a Genizi allocation and generalized variance shares support the same financial interpretation when applied to the same multi-period currency forecast system remains unknown. The question matters because total dependence, net currency positions, and bilateral imbalances combine the same forecast relations in different ways. Agreement at one level need not extend to the others.

3 Forecast system and connectedness measures

3.1 Time-varying parameter vector autoregression

We first estimate one forecast system for the four currency returns and then construct two connectedness measures from its forecast errors. Time-varying parameter VARs allow the predictive relations to evolve over time (Primiceri, 2005; Koop and Korobilis, 2013). The forecast system and horizon remain fixed throughout, so differences between the resulting networks arise from the allocation of correlated forecast-error variation rather than from different exchange-rate dynamics.

Let $\mathbf{y}_t = (y_{1t}, \dots, y_{Nt})'$ collect the N exchange-rate returns. The empirical model is a first-order time-varying parameter vector autoregression (TVP-VAR),

$$\mathbf{y}_t = \mathbf{B}_t \mathbf{y}_{t-1} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{H}_t), \quad (1)$$

Both the propagation matrix $\mathbf{B}_t$ and the innovation covariance $\mathbf{H}_t$ change over time. We estimate them with the forgetting-factor Kalman recursion of Antonakakis et al. (2020), building on the discount-based time variation used in macro-financial conditions models (Koop and Korobilis, 2014). The coefficient state follows a random walk, while λ_B and λ_H , set to 0.99 and 0.96 in the baseline, determine how quickly past information is discounted in the coefficient and covariance updates.

Returns are centred before estimation, so the state equation has no separate time-varying intercept. The one-step prediction error updates $\mathbf{H}_t$ before the updated covariance enters the coefficient update. Baseline initialisation uses ordinary least squares (OLS) estimates from the full sample, so the resulting historical paths are filtered rather than real-time estimates. The robustness analysis replaces this prior with Minnesota and uninformative priors. Supplementary Section A.1 gives the recursion, initialisation, and alternative-prior details.

3.2 Multi-step forecast errors

The forecast at date t holds the current filtered coefficient matrix and innovation covariance fixed over the horizon, because future parameter paths are unknown. The parameters are then updated before the calculation is repeated at $t + 1$, so the forecast relations evolve throughout the sample. Let $\Phi_{t,0} = \mathbf{I}_N$ and construct $\Phi_{t,h}$ recursively from the current coefficient matrix. The associated H -step forecast-error covariance is

$$\Omega_t(H) = \sum_{h=0}^{H-1} \Phi_{t,h} \mathbf{H}_t \Phi_{t,h}'. \quad (2)$$

Both connectedness measures are computed from $\Omega_t(H)$ and therefore summarize uncertainty accumulated over the same H months.

The horizon determines which relations enter the forecast errors. At one month, the covariance is the current innovation covariance; propagation through the current VAR coefficients begins at horizons of two months and longer and becomes increasingly important as the horizon extends. Using the same horizon and common forecast covariance ensures that both networks describe dependence over the same investment period and leaves the decomposition as the only source of difference between them at each date.

3.3 Diebold–Yilmaz connectedness

Diebold–Yilmaz (DY) connectedness decomposes the forecast-error variance of target currency i into contributions from innovations elsewhere in the system. We use the generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998), as applied to connectedness by Diebold and Yilmaz (2012). The unnormalised contribution of source currency j is

$$\tilde{\theta}_{ij,t}^{\text{DY}}(H) = \frac{h_{jj,t}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i' \boldsymbol{\Phi}_{t,h} \mathbf{H}_t \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} \mathbf{e}_i' \boldsymbol{\Phi}_{t,h} \mathbf{H}_t \boldsymbol{\Phi}_{t,h}' \mathbf{e}_i}, \quad (3)$$

where $\mathbf{e}_i$ selects element i . Because the generalized shares do not generally sum to one, they are normalised by row,

$$\theta_{ij,t}^{\text{DY}}(H) = \frac{\tilde{\theta}_{ij,t}^{\text{DY}}(H)}{\sum_{m=1}^N \tilde{\theta}_{im,t}^{\text{DY}}(H)}. \quad (4)$$

The DY total connectedness index is

$$\text{TCI}_t^{\text{DY}}(H) = \frac{100}{N} \sum_{i \neq j} \theta_{ij,t}^{\text{DY}}(H). \quad (5)$$

Row normalisation makes each target equation sum to one, so the off-diagonal entries record the share of a target’s forecast-error variance associated with innovations in the other currencies and TCI averages those shares across targets.

3.4 R^2 connectedness based on the Genizi decomposition

R^2 connectedness uses the correlation structure of the same forecast errors. Standardising (2) gives

$$\mathbf{R}_t(H) = \mathbf{D}_t^{-1/2} \boldsymbol{\Omega}_t(H) \mathbf{D}_t^{-1/2}, \quad \mathbf{D}_t = \text{diag}(\boldsymbol{\Omega}_t(H)). \quad (6)$$

For target i , let $\mathbf{r}_{i,t}$ be its correlations with the $N - 1$ other forecast errors and let $\mathbf{R}_{x,i,t}$ be their correlation matrix; the horizon argument is suppressed in these intermediate quantities. The multiple coefficient of determination is

$$R_{i,t}^2 = \mathbf{r}_{i,t}' \mathbf{R}_{x,i,t}^{-1} \mathbf{r}_{i,t}. \quad (7)$$

When source forecast errors are correlated, their joint explanatory power cannot be assigned by adding separate bivariate fits. Following Genizi (1993), let the symmetric principal square root of their correlation matrix be

$$\mathbf{A}_{i,t} = \mathbf{R}_{x,i,t}^{1/2} = \mathbf{V}_{i,t} \boldsymbol{\Lambda}_{i,t}^{1/2} \mathbf{V}_{i,t}', \quad \mathbf{c}_{i,t} = \mathbf{A}_{i,t}^{-1} \mathbf{r}_{i,t}. \quad (8)$$

The vector of source contributions is

$$\mathbf{g}_{i,t} = \mathbf{A}_{i,t}^{\circ 2} \mathbf{c}_{i,t}^{\circ 2}, \quad g_{ij,t} = \sum_{\ell=1}^{N-1} a_{j\ell,i,t}^2 c_{\ell,i,t}^2, \quad (9)$$

where $\circ 2$ denotes elementwise squaring. Each contribution is nonnegative, and the contributions for target i sum to $R_{i,t}^2$. The off-diagonal connectedness contribution from source j to target i is $\theta_{ij,t}^{R^2} = g_{ij,t}$, while the own component is $\theta_{ii,t}^{R^2} = 1 - R_{i,t}^2$. Averaging the explained shares across targets yields

$$\text{TCI}_t^{R^2}(H) = \frac{100}{N} \sum_{i=1}^N R_{i,t}^2. \quad (10)$$

Here the off-diagonal row sum is already $R_{i,t}^2$, so no additional row normalisation is required. The own component is the share of forecast-error variation not jointly explained by the remaining currencies.

The two measures therefore weight correlated forecast variation differently. DY assigns each generalized share to an individual innovation and then normalises by row; R^2 assigns the joint explanatory power of the other forecast errors and distributes it among them. Because the sources comove, the two allocations need not coincide. The R^2 contributions are nonnegative, sum to the multiple R^2 for each target currency, and are invariant to the ordering of the source currencies. Supplementary Section A.2 gives the fixed-parameter and one-step special cases.

3.5 Directional connectedness measures

For either construction, total directional connectedness from others (FROM) to currency i , total directional connectedness to others (TO) from currency i , and net total directional connectedness (NET) are

$$C_{i,t}^{\leftarrow} = 100 \sum_{j \neq i} \theta_{ij,t}, \quad (11)$$

$$C_{i,t}^{\rightarrow} = 100 \sum_{j \neq i} \theta_{ji,t}, \quad (12)$$

$$\text{NET}_{i,t} = C_{i,t}^{\rightarrow} - C_{i,t}^{\leftarrow}. \quad (13)$$

Net pairwise directional connectedness (NPDC) is

$$\text{NPDC}_{ij,t} = 100 (\theta_{ji,t} - \theta_{ij,t}). \quad (14)$$

A positive value means that currency i contributes more connectedness to currency j than it receives from j .

For R^2 connectedness, $C_{i,t}^{\leftarrow} = 100R_{i,t}^2$ and the own component is $100(1 - R_{i,t}^2)$. TO aggregates currency i 's contributions to the other forecast-error equations, while NET and NPDC compare those contributions across directions.

Total connectedness accumulates contributions in both directions, whereas NET and NPDC take directional differences. Reciprocal links can therefore raise TCI while offsetting in NET, and changes in relative link magnitudes can alter the ranking of currency

248 pairs.

249 The terminology, direction, and units used in the empirical tables and figures are
250 collected in Supplementary Table A1.

251 4 Data and Empirical Setting

252 4.1 Exchange rates and returns

253 The empirical system contains monthly returns on the euro (EUR), pound sterling (GBP),
254 Japanese yen (JPY), and Swiss franc (CHF), each measured against the U.S. dollar.
255 Monthly-average exchange-rate levels come from the Bank of England Statistical Inter-
256 active Database and are expressed as units of the named currency per U.S. dollar (Bank
257 of England, 2026). The sample contains 612 monthly returns from February 1975 to
258 January 2026, calculated as

$$y_{i,t} = 100 [\log(S_{i,t}) - \log(S_{i,t-1})], \quad (15)$$

259 so a positive value denotes depreciation of the named currency against the dollar.

260 JPY is prominent in low-interest-rate funding trades, and JPY and CHF have histor-
261 ically displayed defensive behaviour in periods of market stress (Ranaldo and Söderlind,
262 2010; Habib and Stracca, 2012; Brunnermeier et al., 2008). Quoting all four against the
263 U.S. dollar gives them a common reference currency. The dollar’s central role in trade
264 invoicing, banking, and international asset allocation makes this comparison economically
265 relevant (Gopinath et al., 2020; Gopinath and Stein, 2021; Maggiori et al., 2020), and
266 bilateral exchange rates against the dollar contain substantial common variation (Verdel-
267 han, 2018). The monetary histories and market uses of EUR, GBP, JPY, and CHF
268 nevertheless remain distinct.

269 Monthly averages place currencies traded in different market hours on a common
270 observation frequency and avoid treating closing quotes from different sessions as syn-
271 chronous. This matters in a market with strong intraday periodicity and volatility trans-

mission across trading centres (Engle et al., 1990; Andersen et al., 2001). The averages provide a consistent monthly comparison across the 1975–2026 sample rather than changes between market-specific closing times.

Before 1999, the euro observations come from the Bank of England’s synthetic historical euro series rather than a traded spot rate. The pre-end-1998 observations combine the eleven participating currencies using International Monetary Fund (IMF) weights (Bank of England, 2000). This official backcast permits a continuous comparison of the European position with sterling, the yen, and the Swiss franc through earlier exchange-rate regimes. Because it represents a currency basket rather than post-union euro trading, Section 6 repeats the analysis from January 1999.

The five-decade sample places the August 2024 unwind in the same empirical system as earlier changes in exchange-rate arrangements, global funding conditions, and market stress. The long sample permits comparison of persistent currency roles with behaviour around particular episodes. The post-1999 estimates show separately how the results change when the analysis is restricted to observed euro trading.

Table 1. Summary statistics and return correlations.

<i>Panel A. Distribution and stationarity</i>							
Currency	Mean	Std. dev.	Skewness	Kurtosis	Minimum	Maximum	ADF
EUR	0.02	2.33	0.02	3.41	−6.77	8.06	−7.43***
GBP	0.09	2.35	0.30	4.88	−10.31	11.00	−7.97***
JPY	−0.11	2.62	−0.46	4.10	−10.60	8.10	−7.52***
CHF	−0.19	2.66	−0.06	4.05	−8.24	11.21	−7.76***
<i>Panel B. Return correlations</i>							
Currency	EUR	GBP	JPY	CHF	Average		
EUR	1.00	0.70	0.48	0.86	0.68 / 0.52		
GBP	0.52	1.00	0.34	0.63	0.56 / 0.41		
JPY	0.34	0.26	1.00	0.55	0.46 / 0.32		
CHF	0.70	0.45	0.38	1.00	0.68 / 0.51		

Notes: Monthly log changes in named-currency units per U.S. dollar. Kurtosis is the conventional moment coefficient. ADF denotes the augmented Dickey–Fuller statistic. *** denotes rejection of the unit-root null at the 1 percent level. In Panel B, Pearson correlations appear above the diagonal, Kendall rank correlations below it, and diagonal entries equal 1.00. The final column reports each currency’s average correlation with the other three as Pearson / Kendall. Both correlation measures give the same ordering of currencies.

The four return series have similar unconditional volatility, with standard deviations

between 2.33 and 2.66 percent, but different distributional shapes. JPY returns are negatively skewed, whereas GBP returns are positively skewed and have the highest kurtosis. All four series have heavier tails than a Gaussian benchmark, and ADF tests reject a unit root in every case.

The similarity in marginal volatility helps separate the network evidence from simple differences in the dispersion of returns. No currency is mechanically dominant because its standard deviation is far larger than the others. The more pronounced differences appear in cross-currency correlations and, in the dynamic analysis, in the allocation of correlated forecast-error variation across currencies.

The correlation matrix already shows that common variation is unevenly distributed. EUR and CHF have the highest average Pearson correlations with the other currencies, both about 0.68, followed by GBP at 0.56 and JPY at 0.46; Kendall correlations give the same ordering. The allocation of correlated forecast-error variation is therefore likely to have a larger effect on the estimates for EUR and CHF than on those for JPY.

4.2 Empirical specification

The baseline uses a one-lag TVP-VAR and a 12-month forecast horizon, so dependence is measured in forecast uncertainty accumulated over a year. Forgetting factors of 0.99 for the coefficients and 0.96 for the innovation covariance allow the covariance to adjust faster than the coefficient state. An OLS-based Bayesian prior initializes the recursion. Both connectedness networks use this same sequence of forecast distributions.

The robustness analysis varies each element of this specification in turn. The descriptive comparison in Section 5.4 includes the August 2024 unwind and six earlier episodes. All rates are quoted against the U.S. dollar, so common dollar movements remain part of each estimated network.

5 Empirical Results

5.1 Aggregate dependence across currencies

At the system level, the two connectedness measures follow similar paths over time (Figure 2). Their TCI correlation is 0.918, and the main increases and declines occur at broadly similar dates, although R^2 exceeds DY in 611 of the 612 months. The difference has a standard deviation of 4.47 points and reaches 31.08 points in October 2008. The two measures therefore identify similar changes in dependence across the four currencies, even though they differ in how much forecast uncertainty is associated with the other currencies.

The level difference is concentrated in EUR and CHF. Average total connectedness is 50.68 percent under DY and 60.59 percent under R^2 , a difference of 9.92 percentage points. Table 2 shows that received connectedness rises by 21.03 points for EUR and 19.04 points for CHF, compared with 1.78 points for GBP, while the JPY estimate falls by 2.19 points. Most of the higher R^2 total therefore comes from the two currencies most closely related to the rest of the portfolio.

The unconditional return correlations point to the source of this concentration. EUR and CHF have the highest average Pearson and Kendall correlations with the other currencies, followed by GBP and then JPY (Table 1), and the increases in received connectedness have the same ordering. DY assigns forecast uncertainty to individual innovations, whereas R^2 allocates the variation jointly explained by the other forecast errors, so the choice of decomposition has its largest effect precisely on the currencies that comove most with the rest of the portfolio and its smallest effect on JPY. Supplementary Section A.5 reports a heteroskedasticity- and autocorrelation-consistent standard error and two block-bootstrap confidence intervals for the average difference.

Table 2. Average total connectedness and total directional connectedness from others.

Currency	DY FROM	R^2 FROM	Difference
EUR	58.06	79.09	21.03
GBP	49.20	50.98	1.78
JPY	37.58	35.39	-2.19
CHF	57.87	76.91	19.04
TCI	50.68	60.59	9.92

Notes: DY and R^2 denote TVP-VAR-DY and TVP-VAR- R^2 . Entries are full-sample averages in percent. Difference is R^2 minus DY. Supplementary Table A2 reports the complete connectedness matrices.

The reciprocal EUR–CHF relation accounts for most of the higher system-wide estimate. CHF’s contribution to EUR rises from 29.81 percent under DY to 44.63 percent under R^2 , while EUR’s contribution to CHF rises from 30.34 to 45.01 percent. Together, the two directions account for 29.49 points of the 39.66-point increase across all off-diagonal entries, or 74.34 percent. Earlier foreign-exchange evidence likewise finds close links among European currencies and substantial commonality in currency-market liquidity (Greenwood-Nimmo et al., 2016; Mancini et al., 2013; Karnaukh et al., 2015). Both directions increase together, so the additional dependence weakens diversification between EUR and CHF but largely cancels when inward and outward contributions are subtracted: a portfolio can become more dependent without a comparably large net imbalance between the same positions.

The own components in Supplementary Table A2 show the other side of this change. The EUR own share falls from 41.94 percent under DY to 20.91 percent under R^2 , and the CHF own share falls from 42.13 to 23.09 percent. The decline is much smaller for JPY. The higher R^2 total is therefore not a uniform level shift across the system. It reflects a different assessment of how much variation in the most highly correlated currencies is explained by the rest of the portfolio.

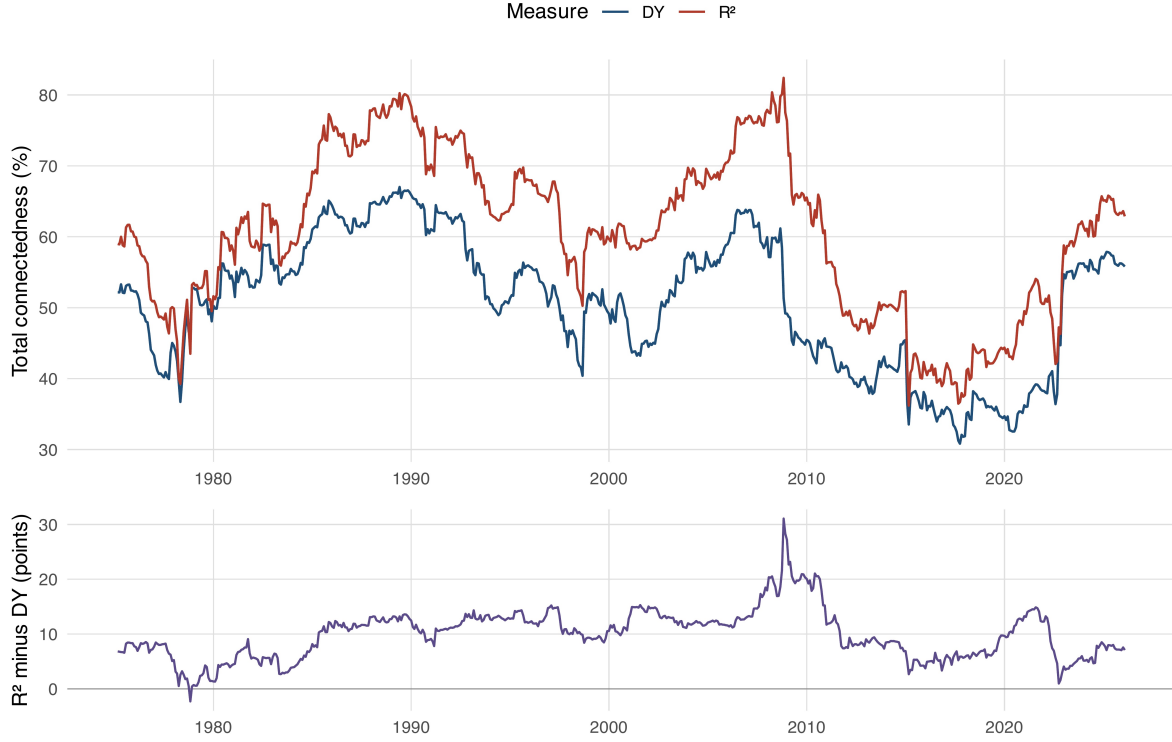


Figure 2. System-wide connectedness under TVP-VAR-DY and TVP-VAR- R^2 . Lines report monthly total connectedness in percent. The lower panel reports $\text{TCI}^{R^2} - \text{TCI}^{\text{DY}}$.

5.2 The distribution across currencies

The average net positions have the same ordering under both measures, but their magnitudes differ. EUR ranks first and CHF second, while GBP and JPY have negative average balances (Table 3). The absolute NET values are uniformly smaller under R^2 , falling from 9.28 to 3.75 for EUR, from 7.58 to 2.99 for CHF, from 8.01 to 2.77 for GBP, and from 8.85 to 3.97 for JPY. Accordingly, the difference between the largest contributor, EUR, and the largest receiver, JPY, narrows from 18.13 points under DY to 7.72 points under R^2 .

Table 3. Average net total directional connectedness.

Currency	NET		Rank		Same sign (%)
	DY	R^2	DY	R^2	
EUR	9.28	3.75	1	1	89.71
GBP	-8.01	-2.77	3	3	91.18
JPY	-8.85	-3.97	4	4	97.39
CHF	7.58	2.99	2	2	81.54

Notes: DY and R^2 denote TVP-VAR-DY and TVP-VAR- R^2 . NET entries are full-sample averages in percentage points. Positive values identify net contributors and negative values net receivers. Ranks run from the largest to the smallest NET; the last column gives the percentage of monthly estimates with the same sign.

The smaller NET balances reflect stronger two-way relations rather than weaker gross dependence. EUR's contribution to the other currencies rises from 67.34 under DY to 82.84 under R^2 , while its received connectedness rises from 58.06 to 79.09; CHF exhibits the same pattern. Much of each increase offsets in the net calculation. EUR and CHF therefore remain net contributors even as their dependence on the rest of the portfolio rises, which is why their ranks can stay stable while the size of the imbalance contracts.

JPY is a net receiver under both measures in 97.39 percent of the months, yet the correlation between its two monthly NET series is only 0.213, and CHF's monthly NET estimates have the same sign in only 81.54 percent of the sample, the lowest share among the four currencies. Average net positions can thus remain stable even when the estimated magnitude, timing, or sign differs in particular months, a pattern wider foreign-exchange networks also display across market states and events (Figure 3) (Greenwood-Nimmo et al., 2025; Huynh et al., 2023; Albrecht and Kočenda, 2025).

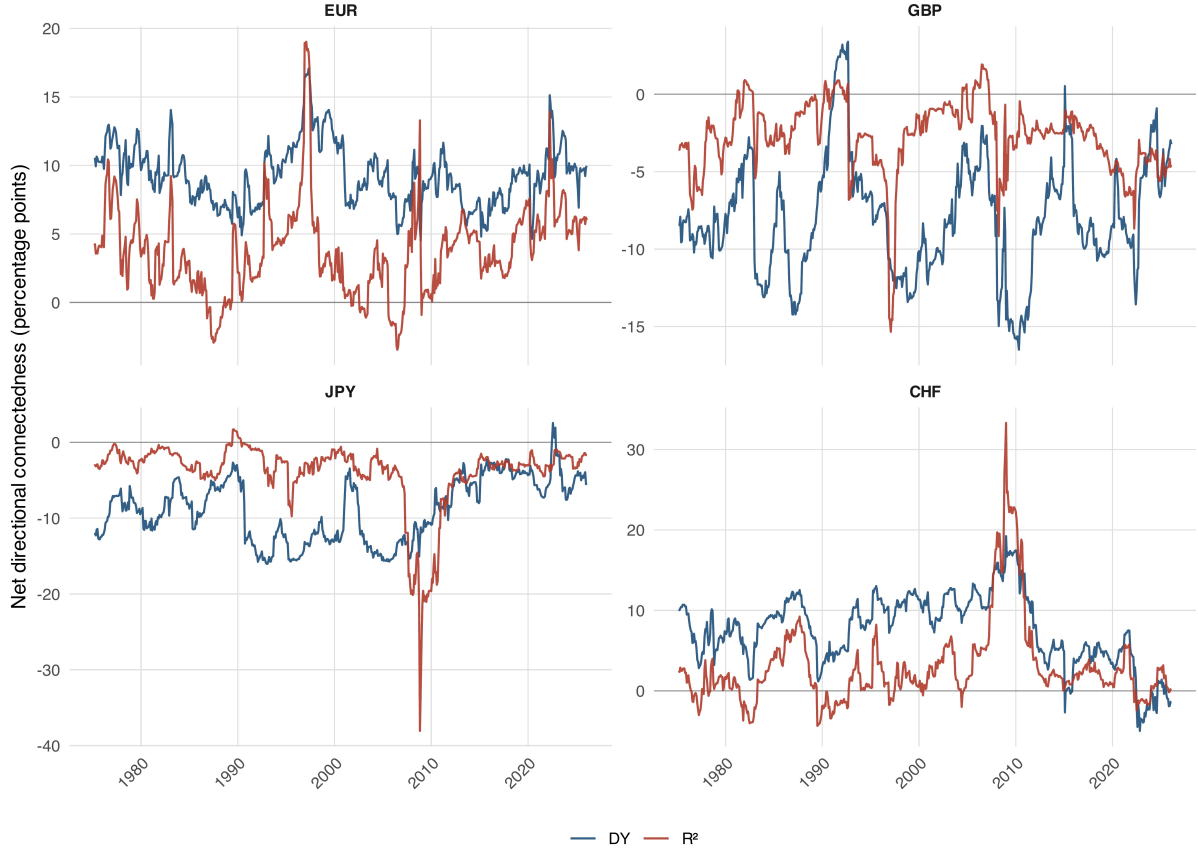


Figure 3. Net total directional connectedness under TVP-VAR-DY and TVP-VAR- R^2 . Lines are monthly NET estimates in percentage points, with no smoothing. Positive values identify net contributors to the connectedness matrix, and negative values identify net receivers. DY and R^2 denote TVP-VAR-DY and TVP-VAR- R^2 , respectively.

5.3 The concentration across currency pairs

The bilateral estimates identify different pairs with the largest average absolute NPDC. EUR–GBP has the largest value under DY, whereas JPY–CHF ranks first under R^2 (Table 4 and Figure 4). The signed means are 5.44 for EUR–GBP under DY and -2.63 for JPY–CHF under R^2 . The first estimate indicates a larger contribution from EUR to GBP; the second indicates a larger contribution from CHF to JPY.

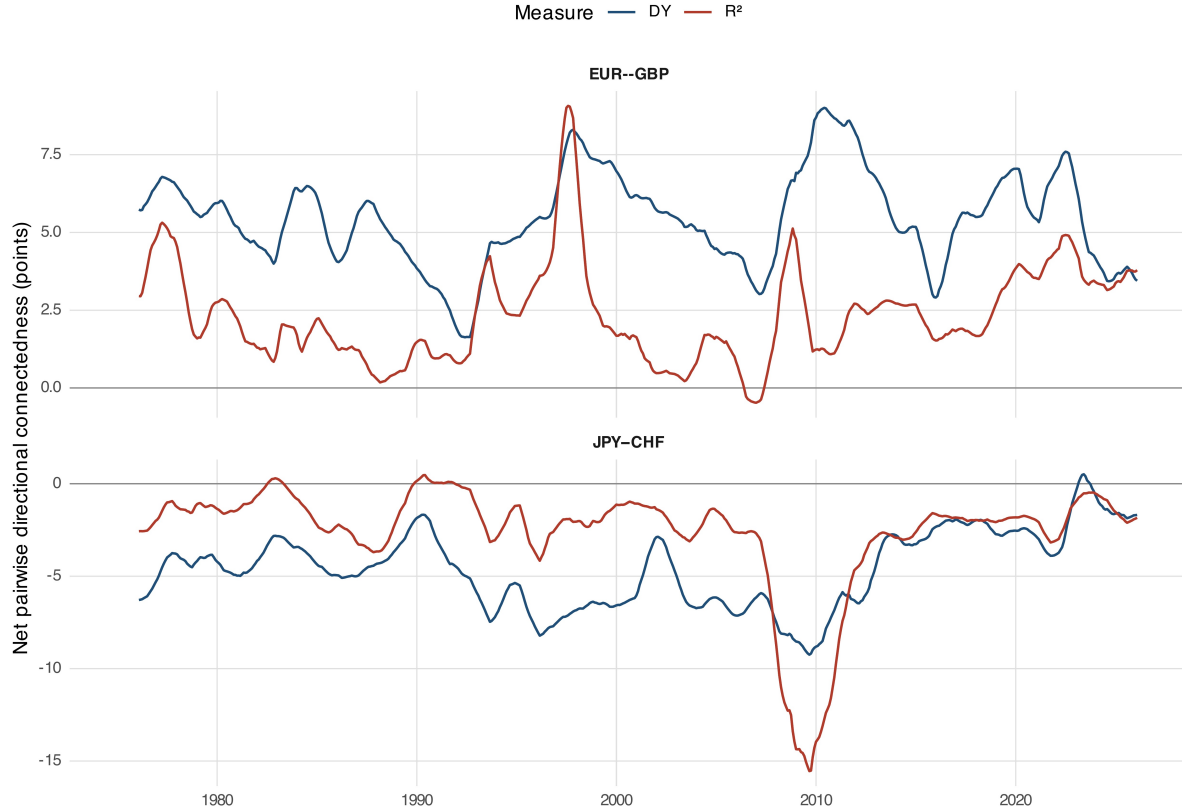


Figure 4. Net pairwise directional connectedness for EUR–GBP and JPY–CHF. Lines are trailing 12-month means of monthly NPDC. Positive values indicate that the first currency contributes more connectedness to the second than it receives from the second. EUR–GBP and JPY–CHF are shown because they rank first under DY and R^2 , respectively. The unsmoothed monthly series are used for all reported statistics.

Table 4. Average net pairwise directional connectedness.

Pair	Mean NPDC		Mean NPDC		Rank		Same sign (%)
	DY	R^2	DY	R^2	DY	R^2	
EUR–GBP	5.44	2.36	5.44	2.38	1	2	97.22
JPY–CHF	−4.60	−2.63	4.63	2.67	2	1	93.46
GBP–CHF	−3.50	−0.73	3.51	0.84	3	5	86.27
EUR–JPY	3.31	1.01	3.31	1.05	4	4	89.22
GBP–JPY	0.93	0.33	1.18	0.45	5	6	72.39
EUR–CHF	0.53	0.38	1.05	1.49	6	3	92.32

Notes: Entries are percentage points. NPDC is the signed full-sample average; positive values indicate a larger contribution from the first currency to the second. |NPDC| is the sample average of absolute monthly NPDC and determines the descending ranks. Same sign is the percentage of unsmoothed monthly estimates with the same sign under the two measures.

The change in the highest-ranked pair is driven by relative magnitude rather than widespread reversals in direction. EUR–GBP has the same sign under the two measures in 97.22 percent of months and JPY–CHF in 93.46 percent. Their average absolute values fall from 5.44 and 4.63 points under DY to 2.38 and 2.67 points under R^2 ; the larger

contraction in EUR–GBP moves it behind JPY–CHF. The lower ranks also change, with GBP–CHF falling from third to fifth and EUR–CHF rising from sixth to third. Across all pairs, same-sign shares range from 72.39 to 97.22 percent. The prevailing direction is usually similar, but the concentration of bilateral dependence is not.

The EUR–CHF entries account for much of the difference between the total and net results. Their average absolute NPDC rises from 1.05 under DY to 1.49 under R^2 , while their signed mean remains small because the two directions are large and similar. Prominent currency relations vary over time, across market states, and with the sampling interval (Baruník et al., 2017; Albrecht and Kočenda, 2024; Rubaszek et al., 2025); here the ranking also changes with the decomposition of correlated forecast errors, even though the two measures move together and the average net ordering remains the same.

5.4 The August 2024 unwind in historical perspective

The August 2024 window shows that DY and R^2 identify different lowest-NET currencies. In the 25-month window centred on the unwind, both place EUR and CHF above GBP and JPY in the NET ordering. DY assigns the lower balance to JPY, whereas R^2 assigns it to GBP (Table 5). The margin between the two values is small, so the different rankings do not alter the identification of GBP and JPY as net receivers. The difference between the two TCIs is 6.58 points, among the smallest across the seven windows.

The monthly estimates show how the difference emerged. In July the two TCIs were 55.40 and 60.13; in August they were 55.20 and 63.06. DY is essentially unchanged, whereas R^2 rises by close to three points. The difference between the two TCIs increases by about two-thirds in one month and remains elevated over the remainder of the sample. At the same time, the net positions of JPY, GBP, and CHF diverge across the two constructions.

The return pattern in Figure 1 does not determine the NET ordering. JPY had by far the largest appreciation during August, but the size of that return does not determine its net position in the connectedness network. The return data show that the adjustment extended beyond JPY; the directional estimates show whether connectedness was

concentrated in JPY or shared with the other currencies.

Two episodes illustrate the contrast between aggregate and directional evidence. During the global financial crisis, the R^2 total exceeds DY by 20.82 points, the largest difference among the seven windows in Table 5; both constructions nevertheless identify CHF as the largest net contributor, and JPY–CHF has the largest average absolute NPDC. The measures differ only on which currency has the lower NET, with R^2 giving JPY a much lower value than DY. Around the Swiss National Bank’s January 2015 exit from the minimum exchange rate, the total difference is only 6.17 points, but the pair with the largest average absolute NPDC changes from EUR–GBP under DY to JPY–CHF under R^2 .

Table 5. Connectedness in selected episodes.

<i>Panel A. Total connectedness</i>						
Episode	DY TCI		R^2 TCI		Difference	
U.S. Dollar Support Program	47.31		49.55		2.24	
Plaza Accord	62.45		72.68		10.23	
ERM Crisis	59.14		71.45		12.31	
Global Financial Crisis	52.83		73.65		20.82	
SNB Minimum Exchange Rate Exit	39.65		45.82		6.17	
COVID-19 Pandemic	34.91		45.20		10.29	
Yen Carry Unwind	56.38		62.96		6.58	
<i>Panel B. Net total and net pairwise directional connectedness</i>						
Episode	Highest NET		Lowest NET		Largest average NPDC	
	DY	R^2	DY	R^2	DY	R^2
U.S. Dollar Support Program	EUR	EUR	GBP	GBP	EUR-GBP	EUR-GBP
Plaza Accord	CHF	CHF	JPY	JPY	JPY-CHF	JPY-CHF
ERM Crisis	EUR	EUR	JPY	JPY	JPY-CHF	EUR-GBP
Global Financial Crisis	CHF	CHF	GBP	JPY	JPY-CHF	JPY-CHF
SNB Minimum Exchange Rate Exit	EUR	EUR	JPY	JPY	EUR-GBP	JPY-CHF
COVID-19 Pandemic	EUR	EUR	GBP	GBP	EUR-GBP	EUR-GBP
Yen Carry Unwind	EUR	EUR	JPY	GBP	EUR-GBP	EUR-GBP

Notes: Entries are averages for 25-month windows containing the reference month and the preceding and following 12 months. Difference is R^2 minus DY. Panel B reports the highest and lowest NET currencies and the pair with the largest average absolute monthly NPDC. EUR and CHF are the two highest-NET currencies and GBP and JPY the two lowest-NET currencies under both measures in every window. Only the order of GBP and JPY differs in the Global Financial Crisis and Yen Carry Unwind windows. ERM denotes Exchange Rate Mechanism, and SNB denotes Swiss National Bank. Reference dates and institutional sources are reported in Supplementary Table A5.

The 2008 window produces the sharpest individual-currency divergence. A broad, funding-driven crisis unwinds leveraged dollar-funding positions across many currencies at once, making the forecast errors of the funding currency and the rest of the portfolio highly correlated (Brunnermeier et al., 2008; Bruno and Shin, 2017; Avdjiev et al., 2019). Under these conditions, R^2 gives JPY a lower NET value than DY, even though GBP and

JPY remain the two lowest-NET currencies. Across the selected episodes, the difference between the two TCIs therefore bears no monotonic relation to currency- or pair-level agreement. The position of GBP and JPY at the lower end of the NET ordering is more stable than the identity of the lowest-NET currency or the pair with the largest average absolute NPDC.

6 Validation and Robustness

Estimator sensitivity is evaluated with Monte Carlo experiments under stable, gradually changing, and directionally reversing population networks. Empirical sensitivity is assessed across alternative estimators, specifications, and sample periods.

6.1 Tracking changes in dependence

Monte Carlo experiments compare TVP-VAR- R^2 with 36-, 60-, and 120-month rolling estimators in stable, smoothly drifting, and directionally reversing four-variable systems. No estimator dominates in every design. Under stability, the 120-month window is most precise, with a total-connectedness root mean squared error of 4.29 points compared with 7.23 for TVP-VAR- R^2 . When the population network moves, the recursive estimator performs better: under smooth drift its error is 8.13 points, compared with 15.21 for the 120-month window. Following a directional reversal, it identifies the population sign in 91.06 percent of the common evaluation sample and detects the reversal with an average delay of 15.59 months, close to the 36-month window and shorter than the delays from longer windows that retain more pre-break information.

These Monte Carlo comparisons reveal a precision–adaptability trade-off rather than a dominant estimator. Long windows gain precision when the population network is stable but adjust slowly when it changes. Recursive discounting responds more closely to smooth drift and sheds pre-break information faster after a reversal, at the cost of greater estimation error under stability. This trade-off supports the time-varying specification for a five-decade sample in which the strength and direction of currency relations can change.

Supplementary Section A.7, Supplementary Table A4, and Supplementary Fig. A5 report the designs, numerical results, and representative paths.

6.2 Stability of the empirical findings

A fixed VAR(1) estimated in 60-month rolling windows replaces recursive discounting with a moving sample (Diebold and Yilmaz, 2009). The R^2 -DY difference is 9.74 points, close to the 9.92-point baseline estimate, and the two rolling TCIs have a correlation of 0.926. The NET ordering is unchanged, while EUR-GBP has the largest average absolute NPDC under DY and JPY-CHF under R^2 . The rolling estimates therefore reproduce the aggregate relation, the NET ordering, and the difference in the pair with the largest average absolute NPDC found with the recursive filter, although their paths are less smooth because the window drops observations after 60 months rather than discounting them recursively. Supplementary Fig. A4 reports the rolling and TVP-VAR paths together.

The horizon, lag length, forgetting factors, and prior leave the aggregate relationship intact (Table 6): average R^2 connectedness remains 7.62 to 10.70 points above DY, and the correlations between the two TCIs remain high. Supplementary Figs. A1–A3 show that these choices mainly affect local smoothness rather than the timing of the principal increases and declines.

At the currency and bilateral levels, however, the conclusions are less uniform. DY and R^2 give the same NET ordering within every specification, although the uninformative prior places CHF above EUR under both measures rather than preserving the baseline order. EUR-GBP has the largest average absolute NPDC under DY and JPY-CHF under R^2 in all but the smoother-dynamics specification, which places EUR-GBP first under both measures. EUR and CHF remain net contributors and GBP and JPY net receivers; the order within those groups and the identity of the pair with the largest average absolute NPDC are the features most sensitive to prior information and the rate of parameter adaptation.

Table 6. Connectedness estimates under alternative specifications.

Specification	TCI		Difference	TCI correlation	Largest average NPDC pair	
	DY	R^2			DY	R^2
Baseline	50.68	60.59	9.92	0.918	EUR-GBP	JPY-CHF
$H = 6$	50.68	60.59	9.92	0.918	EUR-GBP	JPY-CHF
$H = 24$	50.68	60.59	9.92	0.918	EUR-GBP	JPY-CHF
$p = 2$	50.84	60.46	9.62	0.917	EUR-GBP	JPY-CHF
$p = 3$	50.98	59.97	8.99	0.921	EUR-GBP	JPY-CHF
485 Faster adaptation (0.97, 0.94)	51.23	61.93	10.70	0.898	EUR-GBP	JPY-CHF
Smoother dynamics (0.99, 0.99)	51.77	59.38	7.62	0.941	EUR-GBP	EUR-GBP
Minnesota prior	50.46	60.06	9.61	0.908	EUR-GBP	JPY-CHF
Uninformative prior	50.45	59.08	8.63	0.845	EUR-GBP	JPY-CHF
Rolling VAR (60 months)	52.01	61.75	9.74	0.926	EUR-GBP	JPY-CHF

Notes: TCI entries are sample averages in percent. Difference is R^2 minus DY. TCI correlation uses the monthly estimates within each specification. DY and R^2 produce identical NET rankings within every row. The uninformative prior places CHF above EUR under both measures, while all other rows retain the baseline ordering. The final two columns report the pair with the largest average absolute NPDC under DY and R^2 . Before rounding, the horizon estimates differ from the baseline by less than 0.001 percentage points.

6.3 The observed-euro sample

Table 7 reports the estimates for the observed-euro sample. Restricting the sample to observed euro trading from January 1999 yields an average difference of 10.75 points and a TCI correlation of 0.905. Both measures again assign positive NET values to EUR and CHF, although GBP and JPY exchange the third and fourth positions. EUR-GBP has the largest average absolute NPDC under DY, whereas JPY-CHF ranks first under R^2 . The post-1999 estimates therefore preserve the total relation, the NET ordering, and the difference in the pair with the largest average absolute NPDC; only the ordering of the two receivers proves sensitive to the sample period.

Table 7. Connectedness over the post-1999 sample.

<i>Panel A. System-wide connectedness, January 1999–January 2026</i>				
	TCI			
Observations	DY	R^2	Difference	TCI correlation
325	46.12	56.87	10.75	0.905
<i>Panel B. Net total directional connectedness</i>				
	NET		Rank	
Currency	DY	R^2	DY	R^2
EUR	10.10	4.30	1	1
GBP	−9.03	−2.98	4	3
JPY	−6.73	−4.78	3	4
CHF	5.65	3.45	2	2
<i>Panel C. Pair with the largest average absolute NPDC</i>				
Measure	Pair	NPDC		
DY	EUR–GBP	6.42		
R^2	JPY–CHF	3.10		

Notes: TCI and NET entries are sample averages for January 1999–January 2026. Difference is R^2 minus DY. Positive NET values identify net contributors. Panel C ranks currency pairs by the sample average of absolute monthly NPDC, measured in percentage points.

7 Discussion

The August 2024 unwind separates the size of a currency move from its NET position. JPY appreciated far more than the other currencies, but GBP and JPY were both net receivers in the 25-month window centred on the unwind. For investors, a large move in the funding currency is a reason to examine GBP and JPY together rather than infer a single exposed currency from returns alone.

At the portfolio level, TCI records how much forecast uncertainty is shared and therefore how much diversification is lost. NET identifies the currencies that receive more connectedness than they contribute, and NPDC identifies bilateral imbalances. These measures need not be equally stable across decompositions. In this sample, the TCI paths remain similar and GBP and JPY remain net receivers even when their order and the pair with the largest average absolute NPDC change. Under R^2 , both EUR–CHF directions become larger, increasing gross dependence while largely offsetting in NET.

These results complement the literature on currency risk. Common currency and

volatility factors expose investors to common movements in currency returns, whereas hedging benefits vary with currency-specific covariances (Lustig et al., 2011; Menkhoff et al., 2012; Campbell et al., 2010). Portfolio rebalancing, funding constraints, and liquidity conditions can intensify common exchange-rate pressure during an unwind (Hau and Rey, 2006; Gabaix and Maggiori, 2015; Bruno and Shin, 2017; Mancini et al., 2013). NET and NPDC show how connectedness is distributed across currencies and pairs. A currency’s realised return, its funding or defensive role, and its net connectedness describe different aspects of the episode. JPY can therefore dominate the observed return movement even though GBP is also a net receiver.

Alternative estimators, lag lengths, priors, and the post-1999 sample preserve similar TCI paths and identify GBP and JPY as net receivers. The same pattern recurs across the selected episodes, although the 2008 crisis produces the largest difference in JPY’s estimated NET position. Exact currency and pairwise rankings are less stable and do not capture funding costs, hedge payoffs, or exposures elsewhere in the investor’s portfolio.

8 Conclusion

The sharp yen appreciation in August 2024 raised a simple portfolio question about whether connectedness was concentrated in JPY or shared with other currencies. During the unwind window, GBP and JPY were both net receivers, even though their relative order can change. The largest observed return therefore did not show that connectedness was concentrated in JPY.

Across the selected episodes and robustness checks, TCI paths remain similar and GBP and JPY retain negative NET values. The precise currency order and the pair with the largest average absolute NPDC can change with the allocation of correlated forecast-error variation. Holding the forecast system fixed therefore shows which estimates are similar and which are more sensitive to the allocation.

For currency investors, total connectedness indicates when diversification across positions has weakened, while NET shows which currencies receive more connectedness than

537 they contribute. During the 2024 unwind, GBP and JPY were both net receivers, so
538 JPY was not the only receiver. Future research can extend the analysis to alternative
539 numeraire, broader currency sets, and higher-frequency data.

References

- Albrecht, P. and Kočenda, E. (2024). Volatility connectedness on the central european forex markets. *International Review of Financial Analysis*, 93:103179. <https://doi.org/10.1016/j.irfa.2024.103179>.
- Albrecht, P. and Kočenda, E. (2025). Event-driven changes in volatility connectedness in global forex markets. *Journal of Multinational Financial Management*, 77:100896. <https://doi.org/10.1016/j.mulfin.2024.100896>.
- Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2001). The distribution of realized exchange rate volatility. *Journal of the American Statistical Association*, 96(453):42–55. <https://doi.org/10.1198/016214501750332965>.
- Ando, T., Greenwood-Nimmo, M., and Shin, Y. (2022). Quantile connectedness: Modeling tail behavior in the topology of financial networks. *Management Science*, 68(4):2401–2431. <https://doi.org/10.1287/mnsc.2021.3984>.
- Antonakakis, N., Chatziantoniou, I., and Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4):84. <https://doi.org/10.3390/jrfm13040084>.
- Aquilina, M., Lombardi, M. J., Schrimpf, A., and Sushko, V. (2024). The market turbulence and carry trade unwind of August 2024. BIS Bulletin 90, Bank for International Settlements.
- Avdjiev, S., Du, W., Koch, C., and Shin, H. S. (2019). The dollar, bank leverage, and deviations from covered interest parity. *American Economic Review: Insights*, 1(2):193–208. <https://doi.org/10.1257/aeri.20180322>.
- Balli, F., Balli, H. O., Dang, T. H. N., and Gabauer, D. (2023). Contemporaneous and lagged R^2 decomposed connectedness approach: New evidence from the energy futures market. *Finance Research Letters*, 57:104168. <https://doi.org/10.1016/j.frl.2023.104168>.
- Bank of England (2000). Practical issues arising from the euro: November 2000. Bank of England report. The chart note on p. 30 defines the pre-1999 euro exchange rate as U.S. dollars per synthetic euro, using a weighted average of the 11 component currencies with IMF weights; accessed July 27, 2026.
- Bank of England (2026). Statistical interactive database: monthly average spot exchange rates. Bank of England Statistical Interactive Database. Series XUMAERD, XUMAGBD, XUMAJYD, and XUMASFD; accessed July 12, 2026.
- Bank of Japan (2024). Change in the guideline for money market operations and decision on the plan for the reduction of the purchase amount of Japanese government bonds. Bank of Japan statement on monetary policy. accessed July 26, 2026.
- Baruník, J. and Křehlík, T. (2018). Measuring the frequency dynamics of financial

- connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2):271–296. <https://doi.org/10.1093/jjfinec/nby001>.
- Baruník, J., Kočenda, E., and Vácha, L. (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance*, 77:39–56. <https://doi.org/10.1016/j.jimonfin.2017.06.003>.
- Bekaert, G. (1996). The time variation of risk and return in foreign exchange markets: A general equilibrium perspective. *The Review of Financial Studies*, 9(2):427–470. <https://doi.org/10.1093/rfs/9.2.427>.
- Brunnermeier, M. K., Nagel, S., and Pedersen, L. H. (2008). Carry trades and currency crashes. *NBER Macroeconomics Annual*, 23(1):313–348. <https://doi.org/10.1086/593088>.
- Bruno, V. and Shin, H. S. (2017). Global dollar credit and carry trades: A firm-level analysis. *The Review of Financial Studies*, 30(3):703–749. <https://doi.org/10.1093/rfs/hhw099>.
- Bubák, V., Kočenda, E., and Žikeš, F. (2011). Volatility transmission in emerging European foreign exchange markets. *Journal of Banking & Finance*, 35(11):2829–2841. <https://doi.org/10.1016/j.jbankfin.2011.03.012>.
- Camanho, N., Hau, H., and Rey, H. (2022). Global portfolio rebalancing and exchange rates. *Review of Financial Studies*, 35(11):5228–5274. <https://doi.org/10.1093/rfs/hhac023>.
- Campbell, J. Y., Serfaty-de Medeiros, K., and Viceira, L. M. (2010). Global currency hedging. *Journal of Finance*, 65(1):87–121. <https://doi.org/10.1111/j.1540-6261.2009.01524.x>.
- De Bock, R. and de Carvalho Filho, I. (2015). The behavior of currencies during risk-off episodes. *Journal of International Money and Finance*, 53:218–234. <https://doi.org/10.1016/j.jimonfin.2014.12.009>.
- Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1):1–15. <https://doi.org/10.1002/jae.2585>.
- Diebold, F. X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534):158–171. <https://doi.org/10.1111/j.1468-0297.2008.02208.x>.
- Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66. <https://doi.org/10.1016/j.ijforecast.2011.02.006>.
- Diebold, F. X. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134. <https://doi.org/10.1016/j.jeconom.2014.04.012>.
- Du, W., Tepper, A., and Verdelhan, A. (2018). Deviations from covered interest rate parity. *Journal of Finance*, 73(3):915–957. <https://doi.org/10.1111/jofi.12620>.
- Engle, R. F., Ito, T., and Lin, W.-L. (1990). Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica*, 58(3):525–542. <https://doi.org/10.2307/2938189>.
- Evans, M. D. D. and Lyons, R. K. (2002). Order flow and exchange rate dynamics. *Journal of Political Economy*, 110(1):170–180. <https://doi.org/10.1086/324391>.

- Farhi, E. and Gabaix, X. (2016). Rare disasters and exchange rates. *The Quarterly Journal of Economics*, 131(1):1–52. <https://doi.org/10.1093/qje/qjv040>.
- Froot, K. A. and Ramadorai, T. (2005). Currency returns, intrinsic value, and institutional-investor flows. *The Journal of Finance*, 60(3):1535–1566. <https://doi.org/10.1111/j.1540-6261.2005.00769.x>.
- Gabaix, X. and Maggiori, M. (2015). International liquidity and exchange rate dynamics. *Quarterly Journal of Economics*, 130(3):1369–1420. <https://doi.org/10.1093/qje/qjv016>.
- Gabauer, D., Chatziantoniou, I., and Stenfors, A. (2023). Model-free connectedness measures. *Finance Research Letters*, 54:103804. <https://doi.org/10.1016/j.frl.2023.103804>.
- Genizi, A. (1993). Decomposition of R^2 in multiple regression with correlated regressors. *Statistica Sinica*, 3:407–420.
- Gopinath, G., Boz, E., Casas, C., Díez, F. J., Gourinchas, P.-O., and Plagborg-Møller, M. (2020). Dominant currency paradigm. *American Economic Review*, 110(3):677–719. <https://doi.org/10.1257/aer.20171201>.
- Gopinath, G. and Stein, J. C. (2021). Banking, trade, and the making of a dominant currency. *Quarterly Journal of Economics*, 136(2):783–830. <https://doi.org/10.1093/qje/qjaa036>.
- Greenwood-Nimmo, M., Nguyen, V. H., and Rafferty, B. (2016). Risk and return spillovers among the G10 currencies. *Journal of Financial Markets*, 31:43–62. <https://doi.org/10.1016/j.finmar.2016.05.001>.
- Greenwood-Nimmo, M., Steenkamp, D., and Van Jaarsveld, R. (2025). Risk and return spillovers among developed and emerging market currencies. *Journal of International Financial Markets, Institutions and Money*, 98:102086. <https://doi.org/10.1016/j.intfin.2024.102086>.
- Grise, C. and Nitschka, T. (2015). On financial risk and the safe haven characteristics of swiss franc exchange rates. *Journal of Empirical Finance*, 32:153–164. <https://doi.org/10.1016/j.jempfin.2015.03.006>.
- Habib, M. M. and Stracca, L. (2012). Getting beyond carry trade: What makes a safe haven currency? *Journal of International Economics*, 87(1):50–64. <https://doi.org/10.1016/j.jinteco.2011.12.005>.
- Hau, H. and Rey, H. (2006). Exchange rates, equity prices, and capital flows. *The Review of Financial Studies*, 19(1):273–317. <https://doi.org/10.1093/rfs/hhj008>.
- Huynh, T. L. D., Nasir, M. A., and Nguyen, D. K. (2023). Spillovers and connectedness in foreign exchange markets: The role of trade policy uncertainty. *The Quarterly Review of Economics and Finance*, 87:191–199. <https://doi.org/10.1016/j.qref.2020.09.001>.
- Jurek, J. W. (2014). Crash-neutral currency carry trades. *Journal of Financial Economics*, 113(3):325–347. <https://doi.org/10.1016/j.jfineco.2014.05.004>.
- Karnaukh, N., Rinaldo, A., and Söderlind, P. (2015). Understanding FX liquidity. *The Review of Financial Studies*, 28(11):3073–3108. <https://doi.org/10.1093/rfs/hhv029>.
- Koop, G. and Korobilis, D. (2013). Large time-varying parameter VARs. *Journal of Econometrics*, 177(2):185–198. <https://doi.org/10.1016/j.jeconom.2013.04.007>.

- Koop, G. and Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, 71:101–116. <https://doi.org/10.1016/j.euroecorev.2014.07.002>.
- Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147. [https://doi.org/10.1016/0304-4076\(95\)01753-4](https://doi.org/10.1016/0304-4076(95)01753-4).
- Lastrapes, W. D. and Wiesen, T. F. (2021). The joint spillover index. *Economic Modelling*, 94:681–691. <https://doi.org/10.1016/j.econmod.2020.02.010>.
- Lettau, M., Maggiori, M., and Weber, M. (2014). Conditional risk premia in currency markets and other asset classes. *Journal of Financial Economics*, 114(2):197–225. <https://doi.org/10.1016/j.jfineco.2014.07.001>.
- Lustig, H., Roussanov, N., and Verdelhan, A. (2011). Common risk factors in currency markets. *Review of Financial Studies*, 24(11):3731–3777. <https://doi.org/10.1093/rfs/hhr068>.
- Lustig, H. and Verdelhan, A. (2007). The cross section of foreign currency risk premia and consumption growth risk. *American Economic Review*, 97(1):89–117. <https://doi.org/10.1257/aer.97.1.89>.
- Maggiori, M. (2017). Financial intermediation, international risk sharing, and reserve currencies. *American Economic Review*, 107(10):3038–3071. <https://doi.org/10.1257/aer.20130479>.
- Maggiori, M., Neiman, B., and Schreger, J. (2020). International currencies and capital allocation. *Journal of Political Economy*, 128(6):2019–2066. <https://doi.org/10.1086/705688>.
- Mancini, L., Rinaldo, A., and Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *The Journal of Finance*, 68(5):1805–1841. <https://doi.org/10.1111/jofi.12053>.
- Melvin, M. and Taylor, M. P. (2009). The crisis in the foreign exchange market. *Journal of International Money and Finance*, 28(8):1317–1330. <https://doi.org/10.1016/j.jimonfin.2009.08.006>.
- Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A. (2012). Carry trades and global foreign exchange volatility. *Journal of Finance*, 67(2):681–718. <https://doi.org/10.1111/j.1540-6261.2012.01728.x>.
- Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review*, 47(2):527–556. <https://doi.org/10.1111/j.1468-2354.2006.00387.x>.
- Pesaran, M. H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1):17–29. [https://doi.org/10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0).
- Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72(3):821–852. <https://doi.org/10.1111/j.1467-937x.2005.00353.x>.
- Rinaldo, A. and Söderlind, P. (2010). Safe haven currencies. *Review of Finance*, 14(3):385–407. <https://doi.org/10.1093/rof/rfq007>.
- Rigana, K., Wit, E.-J. C., and Cook, S. (2023). A new way of measuring effects of

- financial crisis on contagion in currency markets. *International Review of Financial Analysis*, 90:102764. <https://doi.org/10.1016/j.irfa.2023.102764>.
- Rubaszek, M., Szafranek, K., and Uddin, G. S. (2025). Intraday volatility connectedness on the forex market: The role of uncertainty. *Journal of International Money and Finance*, 157:103398. <https://doi.org/10.1016/j.jimonfin.2025.103398>.
- Sato, A., Nakata, H., and Percy, J. (2024). Time-variant safe haven currencies. *International Review of Economics & Finance*, 93:316–328. <https://doi.org/10.1016/j.ieref.2024.04.015>.
- Verdelhan, A. (2018). The share of systematic variation in bilateral exchange rates. *Journal of Finance*, 73(1):375–418. <https://doi.org/10.1111/jofi.12587>.
- Zhu, H., Deng, X., Ren, Y., and Huang, X. (2024). Time-frequency co-movement and cross-quantile connectedness of exchange rates: Evidence from ASEAN+3 countries. *Quarterly Review of Economics and Finance*, 98:101920. <https://doi.org/10.1016/j.qref.2024.101920>.

Data Availability

The analysis uses Bank of England series XUMAERD, XUMAGBD, XUMAJYD, and XUMASFD. These series are publicly available from the Bank of England Statistical Interactive Database. The accompanying anonymised replication package contains the original series, the processed monthly-return data used in the analysis, documentation of the variable definitions and data transformations, and the code required to reproduce the reported tables and figures, including the Monte Carlo simulations.

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

Informed consent was not required because this article does not contain any studies with human participants.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryInformation.pdf](#)
- [AnonymousReplicationPackage.zip](#)