Risk and Return Spillovers in a Global Model of the Foreign Exchange Network

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Risk and Return Spillovers among Developed and Emerging Market Currencies[*†]

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We develop a network model capturing the dynamic interactions among foreign exchange (FX) returns and realized risk measures for 20 developed market (DM) and emerging market (EM) currencies. We show that DM currencies are more integrated within the network than EM currencies on average and tend to become more dependent on external conditions over time. Spillovers between DMs and EMs evolve more rapidly than spillovers within DMs and within EMs and are a major contributor to overall spillover dynamics. Auxiliary regressions reveal that the net DM-to-EM spillover comoves with global factors known to drive EM capital flows.

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1 Introduction

The question of how to allocate and rebalance capital between DM and EM currencies is central to the investment strategies of many FX investors. Several stylized features of DM and EM economies are widely understood to affect FX portfolio management decisions, including the observation that capital typically flows into (out of) EMs in periods of high (low) investor risk appetite and when yields in developed markets are low (high) and that episodes of contagion are associated with EM capital flow retrenchments (e.g., Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012; Fratzscher et al., 2018). However, these aggregate observations may obscure a more subtle network of interactions between the risk-return profiles of DM and EM currencies that are also relevant to investors. To study these interactions, we develop and estimate an empirical network model that captures risk and return spillovers among 20 of the most actively traded and liquid currencies in the world over the period from 2006-07-12 to 2021-12-31, including 12 DM currencies and 8 EM currencies.

Our analysis builds on that of Greenwood-Nimmo et al. (2016, hereafter GNR), who develop a network model to characterize risk and return spillovers among the G10 currencies over the period from January 1999 to October 2014. Our approach differs from theirs in several important respects. First, unlike GNR, who focus on DM currencies, we consider a broad cross-section of DM and EM currencies with the explicit objective of studying spillovers between the two groups. Second, we consider a more recent sample period, covering a number of major events that have occurred since the end of the GNR data set, including the COVID pandemic. Third, unlike GNR, who study higher-order FX moments using the moments of the option-implied (risk-neutral) distribution of future exchange rate changes for each currency, we work with realized moments. This choice is necessitated by our desire to study a large cross-section of currencies including many EM currencies, several of which do not have sufficiently liquid FX options markets to yield reliable estimates of risk-neutral moments. Finally, given that our model includes EM currencies that may be more prone to extreme movements than their DM counterparts, our model includes the first four moments of the return distribution, while GNR exclude return kurtosis from their analysis.

We being by constructing a daily database of log-returns and higher-order realized moments for 20 major currencies quoted against the US dollar over the period from July 2006 to December 2021 using intraday data from Refinitiv. Working with mid-rates sampled at 5-minute intervals to balance precision in construction of the moments against concerns about microstructure noise (see also Do et al., 2016), we compute the first four realized moments of the return distribution at daily frequency: the log-return, realized variance, skewness and kurtosis. We then extract the innovations in the realized moments using auxiliary first-order autoregressions, following the precedent of Menkhoff et al. (2012), Chang et al. (2013) and GNR.

To analyze the network structure of FX returns and risk innovations, we use the generalized connectedness framework of Greenwood-Nimmo et al. (2021), which is an extension of the network methodology developed by Diebold and Yilmaz (2009, 2014). Diebold and Yilmaz were the first to explore the network structure of the matrix of forecast error variance (FEV) decompositions obtained from an unrestricted reduced form vector autoregression (VAR). Greenwood-Nimmo et al. demonstrate that by subtly modifying the normalization applied to the FEV decompositions by Diebold and Yilmaz, one obtains a network representation that is well-suited to arbitrary aggregations of the connectedness matrix. This matters for our purposes, as it allows us to switch our frame of reference from the level of individual variables, to the currency-level and to the level of currency groups (e.g., the DM or EM currency groups), all while maintaining the comparability of the estimated spillover effects. In addition, given the high-dimensional nature of our model and the typical practice of estimating financial network models over rolling-samples, which limits the number of observations that can be used to fit the model, we set aside classical estimators such as ordinary least squares in favor of the Least Absolute Shrinkage and Selection Operator (LASSO) of Tibshirani (1996). This reduces the number of freely estimated parameters by allowing irrelevant predictors to be excluded from the model on an equation-by-equation basis, an approach that accords with current practice in the financial connectedness literature (e.g., Demirer et al., 2017; Greenwood-Nimmo et al., 2019; Bostanci and Yilmaz, 2020; Greenwood-Nimmo and Tarassow, 2022).

Our analysis proceeds in two parts. First, we establish a benchmark by analyzing the structure of the FX network over the full sample, from July 2006 to December 2021. This provides a picture of the average structure of the FX network over our sample period. This reveals that spillovers within moment groups (e.g., return-to-return spillovers, variance-to-variance spillovers etc.) are generally stronger than spillovers between moment groups (e.g., variance-to-return spillovers) but that strong cross-moment spillover effects also exist. Consequently, the common practice of estimating separate network models for returns and risk measures (e.g., Diebold and Yilmaz, 2009, who estimate separate models of equity return spillovers and volatility spillovers) may result in mis-specification of the network model, as cross-group spillovers that are not estimated are implicitly set to zero. Likewise, while within-currency spillovers (e.g., the spillover from currency i volatility to the return on currency i) are typically stronger than cross-currency spillovers (e.g., the spillover from currency i volatility to the return on currency j), cross-currency spillovers are not negligible. In fact, under aggregation, cross-currency spillovers account for the majority of systemwide FEV over the full sample, at 58.5%. We also observe a clear difference in the behavior of DM and EM currencies over the full sample. DM currencies tend to be more influential than their EM counterparts in the sense that they create stronger outward spillovers. In addition, DM currencies are more integrated within the FX network in the sense that a greater proportion of their FEV is explained by inward spillovers than is the case for EM currencies. On average, DM-to-EM spillovers exceed EM-to-DM spillovers by 2.7 percentage points, indicating that EM currencies as a group are net recipients of DM currency shocks on average over the full sample.

Next, we analyze time-variation in the pattern and intensity of spillovers using rolling samples of 250 trading days. We find that currency markets become more strongly interconnected during periods of stress, in keeping with the results of Bubák et al. (2011) for EM currencies and GNR for DM currencies.[1] GNR argue that this may reflect more frequent or more substantial portfolio rebalancing by FX investors during volatile periods, when risk appetite may decline and liquidity may become a binding constraint. What is new is our finding that the time-varying pattern of spillover activity is strongly influenced by bilateral spillovers among DMs and EMs, which tend to change more rapidly than DM-to-DM and EM-to-EM spillovers. A plausible explanation for the rapid adjustment of bilateral DM/EM spillovers lies in the stylized fact that net capital flows from DMs to EMs are volatile and prone to reversal during periods of elevated uncertainty and reduced risk appetite (e.g., Forbes and Warnock, 2012, and the references therein). This suggests that investors rebalancing away from EMs may contribute to the elevated FX connectedness that we observe in times of stress. We provide indirect evidence of this phenomenon via an auxiliary regression exercise, which reveals that a set of global push factors that are believed to drive capital flows to EMs can explain more than 40% of variation in the net DM-to-EM spillover. To the best of our knowledge, ours is the first study to provide statistical evidence on the linkage between bilateral DM/EM spillover activity and the factors that drive capital flows between DMs and EMs and adds to the evidence of a link between FX connectedness and trade policy uncertainty put forth by Huynh et al. (2020).

This paper proceeds as follows. In Section 2, we provide a concise literature review. In Section 3, we discuss the construction and cleaning of our dataset. In Section 4 we outline our estimation methodology. We present and discuss our results in Section 5 and we conclude in Section 6. Additional details are provided in an Appendix, while an Online Supplement provides further information on our data cleaning routine.

[1] It is also consistent with evidence from other asset classes, including equity (e.g., Diebold and Yilmaz, 2009; Demirer et al., 2017) and credit derivatives (e.g., Greenwood-Nimmo et al., 2019; Bostanci and Yilmaz, 2020; Ando et al., 2022).

2 Literature Review

In a seminal contribution to the literature on FX spillovers, Engle et al. (1990) reject the so-called *heatwave* hypothesis that news has localized country-specific effects in favor of the *meteor shower* hypothesis that intraday volatility spillovers exist across markets. This has the important implication that the moments of the exchange rate return distribution can serve to transmit information among markets. This result has since been widely studied. Using an LM testing procedure robust to high levels of kurtosis in the data, Baillie and Bollerslev (1991) do not find evidence of systematic volatility spillovers in their analysis of four major floating currencies. By contrast, Hong (2001) proposes a novel procedure to test for Granger-type causality in variance, and finds evidence of volatility spillovers among the German mark and Japanese yen. Melvin and Melvin (2003) study high-frequency data for five distinct regions (Asia, the Asia-Europe overlap, Europe, the Europe-America overlap and America) and find evidence of both within-region heatwave effects and cross-region meteor shower effects, with the former being stronger. Likewise, Cai et al. (2008) also study high-frequency data for the same five regions and again find within-region effects to be the more economically significant factor.

Since the publication of the DY method in 2009, it has been widely applied to the analysis of FX volatility transmission. Examples include Bubák et al. (2011), Diebold and Yilmaz (2015), Huynh et al. (2020), Wen and Wang (2020) and Wang et al. (2023). The evidence from this literature points to the existence of clusters in the global FX network (e.g Diebold and Yilmaz, 2015, identify a cluster of five strongly connected European currencies) and highlights time-variation in the intensity of FX volatility spillovers, which tend to increase in times of stress. Baruník et al. (2017) and Baruník and Kočenda (2019) both consider asymmetric generalizations of the DY method based on realized semi-variances, which provide a means of integrating information on the sign of returns into the calculation of their variance, thereby providing a distinction between 'good volatility' and 'bad volatility'. More recently, Gabauer (2020) proposes an alternative to the popular DY method in which volatility impulse response functions are computed from a DCC-GARCH model, and provides evidence of time-varying volatility spillovers among the Swiss franc, the euro, Sterling and the Japanese yen.

While there is a large literature on FX volatility spillovers, studies of higher-moment spillovers among FX markets are rare. This is despite wide recognition of the importance of the higher-order moments of the returns distribution for portfolio allocation and risk management. For example, Scott and Horvath (1980) describe general conditions under which investors will exhibit preferences over skewness and kurtosis. In practice, many FX investors will exhibit a preference for skewness in a desired direction and an aversion to both volatility and kurtosis.

Furthermore, as Jondeau and Rockinger (2000) note, given that skewness and kurtosis characterize the tail behavior of the return distribution, they are important for the measurement of value-at-risk, which is fundamental to modern risk management practices. Consequently, it is surprising that so little published research has considered skewness and kurtosis spillovers in the FX market.

Based on the analysis of generalized impulse response functions obtained from a fractionally integrated VAR model, Do et al. (2016) provide evidence on the nature and extent of realized volatility, skewness and kurtosis spillovers among FX markets. They note an interesting difference in the behavior of DMs and EMs, in the sense that they find stronger evidence of realized volatility and kurtosis spillovers among DMs than EMs. Meanwhile, GNR construct a network model using option-implied estimates of the higher-order moments for the G10 currencies to analyze spillovers among returns, risk-neutral volatility and risk-neutral skewness innovations. Their results indicate that the intensity of FX risk and return spillovers increases in bad states of the world, often spiking in conjunction with large movements in the VIX, the TED spread and the federal funds rate. This suggests that systematic risk factors play an important role in driving FX risk and return spillovers.

The insights derived from this literature have important implications for portfolio diversification, portfolio rebalancing and hedging strategies (Baruník et al., 2017). For example, in his analysis of volatility spillovers among equity and FX markets, Kanas (2000) argues that volatility spillovers may increase the non-systematic risk faced by international investors, thereby reducing the gains from diversification. Likewise, GNR argue that increased skewness spillovers among currencies raise the risk of coordinated crashes of the type studied by Rafferty (2012), which raises the incentive for carry traders to hedge against crash risk. Meanwhile, the differences in the spillover behavior of DM and EM currencies documented by Do et al. (2016) raise interesting questions about the potential diversification benefits of combining DM and EM currency investments. Progress on methods to formalize the use of connectedness measures for portfolio management has recently been made by Broadstock et al. (2022).

3 The Dataset

All of the exchange rate data that we use is expressed in units of foreign currency per US dollar (USD).[2] In selecting which currencies to include in our sample, we balance two considerations. First, we seek to ensure that the currencies in our sample are heavily traded. This is important,

[2]Maintaining consistency in the quoting convention across currencies facilitates comparisons of higher-order risk measures across currencies. The currency abbreviations that we use conform to the alpha codes in the ISO 4217 standard published by the International Organization for Standardization.

because we rely on there being enough intraday variation in quoted bid and ask prices to obtain accurate estimates of the higher-order realized moments for each currency. We proceed by selecting every currency that accounts for 1% or more of over-the-counter (OTC) FX turnover (excluding the USD), as reported in the 2019 triennial survey of turnover in foreign exchange markets published by the Bank for International Settlements.[3] This yields a sample of 19 of the world's most heavily traded currencies, with 12 DM and 7 EM currencies. Our second consideration is to ensure that our sample achieves good global FX coverage, with a representative set of DM and EM currencies from each major region. This draws attention to an omission from the 19 currency pairs selected so far—there is no currency of any EM in the European Union. Consequently, we add USDPLN to our sample, which has the 23rd highest OTC FX turnover (at 0.6% on a net-net basis) and which has a long history of high-quality intraday FX data available from Refinitiv. Consequently, we arrive at a sample of $M = 20$ currency pairs.[4]

Our sample contains the following 12 DM currencies: the Australian dollar (USDAUD), the Canadian dollar (USDCAD), the Swiss franc (USDCHF), the euro (USDEUR), the British pound (USDGBP), the Hong Kong dollar (USDHKD), the Japanese yen (USDJPY), the Korean won (USDKRW), the New Zealand dollar (USDNZD), the Norwegian krone (USDNOK), the Swedish krona (USDSEK), and the Singaporean dollar (USDSGD). In addition, our sample includes the following 8 EM currencies: the Brazilian real (USDBRL), the Chinese renminbi (USDCNY)[5], the Indian rupee (USDINR), the Mexican peso (USDMXN), the Polish złoti (USDPLN), the Russian ruble (USDRUB), the Turkish lira (USDTRY), and the South African rand (USDZAR). Note that our classification of DMs and EMs is consistent with the distinction between 'advanced economies' and 'emerging market and developing economies' adopted by the International Monetary Fund (2020).

For each currency, we use intraday data over the period 2006-07-12 to 2021-12-31 to char-

[3]See Table 2 of the report, available via https://www.bis.org/statistics/rpfx19_fx.pdf.

[4]Other studies of FX connectedness have used larger datasets, including Wang et al. (2023) who study 30 currencies and Wen and Wang (2020), who analyze 65 currencies. However, our sample size is comparable to those of other studies using high-frequency data, such as Baruník et al. (2017) and Baruník and Kočenda (2019), both of which study six DM FX markets and Do et al. (2016), whose study includes 27 FX markets.

[5]China maintains a managed floating currency framework. The remnimbi is traded in two markets: while the offshore renminbi (USDCNH) is largely based on market trading, the onshore renminbi (USDCNY) is regulated and only allowed to trade within a 2 percent range from a given value that is set each day at 9.15 am. The framework has evolved over time. Between July 2005 and July 2008, the currency referenced a basket of currencies and a fixed trading band; between July 2008 and June 2010, the CNY was fixed to the USD; after July 2010 the managed float was reinstated and the trading band gradually expanded (from 0.3 percent between January 1994 and May 2007, then 0.5 percent to April 2012, then 1 percent to March 2014 and thereafter it was set at its current level of 2 percent). The fixing mechanism has gradually changed as well to shift to a more market-determined exchange rate. The current regime, implemented in August 2018, bases the daily midpoint rate on the close of CNY against a basket of currencies on the previous day and quotes from inter-bank dealers, along with a countercyclical adjustment that gives authorities flexibility to affect the level of the exchange rate. Unfortunately the CNH is only available from February 2011 in our dataset, so we are constrained to working with the CNY in order to include the GFC in our sample. However, the CNY and CNH are highly correlated over our sample period and share similar dynamics.

acterize the distribution of exchange rate returns at daily frequency. While it is possible to obtain data on the returns and a variety of higher-moment risk measures for each currency from commercial data providers, we elect to construct our own measures using high-frequency intraday data from Refinitiv. The benefit of this approach is that it affords us precise control at all stages of data-cleaning and moment construction, which results in higher-quality estimates of the realized moments with fewer outliers.

We begin by constructing mid-rates as the mid-point of the bid and ask prices at intraday five-minute intervals. This results in $n = 288$ intraday observations. We then use these intraday mid-rates to compute the first four realized moments of the return distribution at daily frequency: the log-return, realized variance, skewness and kurtosis. The use of a five-minute sampling frequency balances asymptotic considerations in the estimation of the realized moments against the adverse impact of microstructure noise.[6] We consider a trading day to start at 21:05GMT and to end at 21:00GMT and we remove weekends from our sample, as well as a selection of fixed and floating public holidays in the US (see Andersen et al., 2003, for a similar approach). The daily log-return for currency i on day t is obtained as follows:

$$r_{it} = \sum_{j=1}^{n} r_{it,j},$$

where $r_{it,j} = \log\left(p_{it,j}/p_{it,j-1}\right)$ is the jth period-to-period intraday log-return, with $p_{it,j}$ denoting the jth intraday mid-rate. A simple estimator of the realized variance of returns for the ith currency is obtained as the sum of squared intraday returns:

$$UV_{it} = \sum_{j=1}^{n} r_{it,j}^{2}.$$

It is common to scale the realized variance by the number of trading days per year, N, to obtain the following annualized variance measure:

$$V_{it} = N \cdot UV_{it}.$$

The realized variance captures the dispersion of returns, which is a measure of uncertainty.

[6] While one may use data sampled at 30-minute intervals to compute the realized variance, this would only provide 48 intraday observations, which may be inadequate to obtain reliable estimates of the higher-order realized moments that we study. To verify that our treatment of the data does not introduce undesirable distortions, we conducted a careful comparison of our risk and return measures against corresponding series obtained from Bloomberg. In general, our measures are very similar to their Bloomberg counterparts. The principal differences are observed in the higher-order realized moments, with our estimates exhibiting fewer large outliers than their Bloomberg equivalents. This reflects differences in our approach to data cleaning relative to Bloomberg, as well as our use of a 5-minute sampling frequency as opposed to the 30-minute sampling frequency used by Bloomberg. A detailed comparison is available from the authors on request.

Realized skewness measures the degree of asymmetry of the returns distribution and can be estimated as follows:

$$Q_{it} = \sqrt{n} \sum_{j=1}^{n} r_{it,j}^3 \Big/ (UV_{it})^{3/2}.$$

Under our quoting convention, $Q_{it} > 0$ implies that there is a tendency toward depreciation of currency i against the USD, while $Q_{it} < 0$ reveals a tendency toward appreciation against the USD. Realized kurtosis can be constructed as follows:

$$K_{it} = n \sum_{j=1}^{n} r_{it,j}^4 \Big/ (UV_{it})^2.$$

The realized kurtosis measures the mass in the tails of the return distribution; larger values of K_{it} indicate a higher probability of extreme exchange rate returns.

A range of standard descriptive statistics for the log-return and the three higher-order realized moments for each currency are reported in Table 1. For convenience, currencies are ordered by DM/EM status first and by alphabetical order of their ISO 4217 alpha codes second. The table reveals that, over our sample period, EM currencies have typically offered investors higher returns than DM currencies at the cost of higher volatility and more pronounced skewness. Realized kurtosis also tends to be higher among EM currencies, reflecting a higher risk of extreme movements of EM currencies. In addition to these general traits of DM and EM currencies, the table also draws attention to several interesting features of specific currencies. For example, both the HKD and CNY are managed currencies, and this is reflected in their low volatility against the USD.

<<< Insert Table 1 about here >>>

To develop intuition for the time series properties of the returns and realized moments, we plot the average of each measure for the DM and EM currency groups in Figure 1. The figure provides visual evidence of several phenomena documented in Table 1—on average, EM currency returns are higher but more volatile than DM currency returns with considerably greater tail mass. In addition, the figure reveals considerable time-variation in the returns and higher-order moments for both the DM and EM currency groups. Returns for both groups exhibit well-defined periods of elevated volatility around the GFC, during the European sovereign debt crisis, following the Brexit vote and with the outbreak of the COVID crisis. These same events are also clearly visible in the realized volatility plots and can be discerned in the realized skewness and realized kurtosis plots.

<<< Insert Figure 1 about here >>>

The figure also draws attention to an issue that we must address prior to estimation of our VAR model—the realized moments display greater persistence than the exchange rate log-returns. To account for this, we follow Menkhoff et al. (2012), Chang et al. (2013) and GNR and isolate the innovations in each of the higher-order moments as the residual from a first-order autoregression. For example, the realized variance innovation for currency i in period t, v_{it}, is estimated as:

$$\hat{v}_{it} = V_{it} - \hat{a}_i + \hat{b}_i V_{it-1}, \tag{1}$$

where $\hat{a}_i$ and $\hat{b}_i$ are the estimated intercept and autoregressive parameters. The set of innovations obtained in this way for the ith currency is denoted v_{it}, q_{it} and k_{it}, with the hat symbols suppressed to avoid notational clutter. Following the approach of GNR, it is the innovations to the realized moments as opposed to their levels that will be used in estimation.

4 Measuring Connectedness via FEV Decomposition

Diebold and Yilmaz (2009) were the first to show that a decomposition of the forecast error variance from a VAR model can be interpreted as a weighted directed network. Their technique has subsequently been generalized by Diebold and Yilmaz (2014) to achieve invariance to the order of the variables in the VAR model and by Greenwood-Nimmo et al. (2021) to facilitate block aggregation of the estimated network. We adopt the aggregation-robust framework of Greenwood-Nimmo et al., because it allows us to switch freely between different levels of aggregation in order to study different aspects of FX connectedness (e.g., spillovers among individual currencies and spillovers among groups of currencies).

Consider a set of currencies indexed by $i = 1, 2, \ldots, M$ observed at daily frequency over time periods indexed by $t = 1, 2, \ldots, T$. For each currency, we observe the daily log-return on the spot exchange rate, expressed in foreign currency units per US dollar, r_{it}. In addition, for each currency, we observe the innovation to the realized variance, skewness and kurtosis of returns, denoted v_{it}, q_{it} and k_{it}, respectively. The 4×1 vector $\boldsymbol{y}_{it} = (r_{it}, v_{it}, q_{it}, k_{it})'$ collects the endogenous variables for the ith currency. The currency-specific variables can be collected into a vector of global variables to obtain $\boldsymbol{y}_t = (\boldsymbol{y}_{1t}, \boldsymbol{y}_{2t}, \ldots, \boldsymbol{y}_{Mt})'$. The dimension of $\boldsymbol{y}_t$ is $d \times 1$, where $d = 4M$.

The first step in constructing our network statistics is to estimate a VAR model that captures the cross-sectional and dynamic interactions among the variables in $\boldsymbol{y}_t$. VARs are typically estimated using classical techniques such as ordinary least squares (OLS). This was the technique adopted by GNR. However, our model is considerably larger and, in a high-dimensional setting such as ours, the overfitting problem associated with unrestricted estimation by OLS can be severe. Consequently, we follow Nicholson et al. (2017) and introduce sparsity into the VAR parameter matrices by implementing the Least Absolute Shrinkage and Selection Operator (LASSO) proposed by Tibshirani (1996).[7] Shrinkage and selection estimators have been used to address the overfitting problem in the financial connectedness literature by Demirer et al. (2017), Greenwood-Nimmo et al. (2019), Bostanci and Yilmaz (2020) and Greenwood-Nimmo and Tarassow (2022), among others.

Nicholson et al. (2017) propose a unified framework for the estimation of large sparse VARs called VARX-L. The VARX-L framework accommodates many alternative sparsity patterns, ranging from the simple case in which predictors are selected in an unstructured manner to several structured settings in which predictors are selected in groups (e.g., by lag). We estimate what Nicholson et al. refer to as a *Basic VARX-L model*, in which the LASSO L_1 penalty term is applied in order to zero out individual elements of the VAR parameter matrices without imposing any structure on the sparsity pattern. A notable benefit of the unstructured approach relative to structured alternatives is its computational tractability, which arises from the separability of the objective function.

Prior to estimation by LASSO, it is advisable to standardize the variables by centering each series and dividing by its standard deviation. This ensures that the magnitude of the penalty term is unaffected by differences in the scale of the variables in $\boldsymbol{y}_t$. The standardized data is denoted $\check{\boldsymbol{y}}_t$. The p-th order reduced form VAR in $\check{\boldsymbol{y}}_t$ is given by:

$$\check{\boldsymbol{y}}_t = \boldsymbol{\mu} + \sum_{j=1}^{p} \boldsymbol{A}_j \check{\boldsymbol{y}}_{t-j} + \boldsymbol{u}_t, \tag{2}$$

where $\boldsymbol{\mu}$ is a $d \times 1$ vector of intercepts, the $\boldsymbol{A}_j$'s are $d \times d$ matrices of unknown autoregressive coefficients and $\boldsymbol{u}_t$ is a $d \times 1$ vector of reduced form errors with mean zero and positive definite covariance matrix $\boldsymbol{\Sigma}$.[8] We estimate (2) by LASSO, with the LASSO penalty parameter being selected optimally for each equation. Although this is more computationally demanding than selecting a single global penalty parameter for the system as a whole, it allows the degree of shrinkage to vary across equations, resulting in greater flexibility in estimation.

For the ith equation of (2), abstracting from deterministic terms and with $p = 1$, the LASSO

[7] A comparison of our key estimation results using OLS and LASSO is available from the authors on request.

[8] In practice, we find that a lag order of $p = 1$ is sufficient to capture the autocorrelation structure in the data, which decreases rapidly beyond lag one for all variables in the system.

solves the following minimization problem:

$$\widehat{\boldsymbol{a}}_i = \arg\min_{a} \left(\sum_{t=1}^{T} \left(\check{y}_{it} - \sum_{j=1}^{d} a_{ij} \check{y}_{j,t-1} \right)^2 + \lambda_i \sum_{j=1}^{d} |a_{ij}| \right), \tag{3}$$

where $\boldsymbol{a}_i$ denotes the ith row of the VAR(1) parameter matrix and where $\lambda_i > 0$ denotes the equation-specific penalty parameter. We select λ_i following the procedure described in Nicholson et al. (2017), using 10 grid points and a grid depth of 50.

The VAR model (2) has the following vector moving average representation:

$$\check{\boldsymbol{y}}_t = \boldsymbol{\alpha} + \sum_{j=0}^{\infty} \boldsymbol{B}_j \boldsymbol{u}_{t-j}, \tag{4}$$

where the $\boldsymbol{B}_j$'s are obtained recursively as $\boldsymbol{B}_j = \boldsymbol{A}_1 \boldsymbol{B}_{j-1} + \boldsymbol{A}_2 \boldsymbol{B}_{j-2} + \ldots$, for $j = 1, 2, \ldots$ with $\boldsymbol{B}_0 = \boldsymbol{I}_d$ and $\boldsymbol{B}_j = \boldsymbol{0}$ for $j < 0$. Pesaran and Shin (1998) show that the h-steps-ahead generalized forecast error variance decomposition (GVD) is given by:

$$\vartheta_{i \leftarrow j}^{(h)} = \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^{h} \left(\boldsymbol{\epsilon}_i' \boldsymbol{B}_\ell \boldsymbol{\Sigma} \boldsymbol{\epsilon}_j \right)^2}{\sum_{\ell=0}^{h} \boldsymbol{\epsilon}_i' \boldsymbol{B}_\ell \boldsymbol{\Sigma} \boldsymbol{B}_\ell' \boldsymbol{\epsilon}_i}, \tag{5}$$

for $i, j = 1, \ldots, d$, where σ_{jj} is the jth diagonal element of $\boldsymbol{\Sigma}$ and $\boldsymbol{\epsilon}_i$ is a $d \times 1$ selection vector, the ith element of which is one with zeros elsewhere. $\vartheta_{i \leftarrow j}^{(h)}$ expresses the proportion of the h-steps-ahead FEV of variable i that can be attributed to shocks in the equation for variable j. The GVD is order-invariant, unlike alternative variance decompositions based on triangular decompositions of the residual covariance matrix. However, because the GVD is based on non-orthogonal disturbances, the sum of the estimated FEV shares may exceed one. For this reason, following Greenwood-Nimmo et al. (2021), we apply the following normalization:

$$\theta_{i \leftarrow j}^{(h)} = \frac{\vartheta_{i \leftarrow j}^{(h)}}{d \sum_{j=1}^{d} \vartheta_{i \leftarrow j}^{(h)}}, \tag{6}$$

which restores a proportional interpretation of the FEV shares. Specifically, $\theta_{i \leftarrow j}^{(h)}$ measures the proportion of the *systemwide* FEV at horizon h accounted for by the contribution of variable j to the FEV of the ith variable.[9]

The h-steps-ahead $d \times d$ connectedness matrix that summarizes the d^2 interactions among

[9]Note that this normalization differs from the normalization proposed by Diebold and Yilmaz (2014) due to the presence of the d in the denominator. The normalization proposed by Greenwood-Nimmo et al. facilitates aggregation of the spillover statistics obtained from the network model, as it ensures that one does not obtain spillovers exceeding 100% after aggregation.

the d variables in $\check{\boldsymbol{y}}_t$ may be written as follows:

$$C^{(h)} \quad = \quad \begin{bmatrix} \theta^{(h)}_{1\leftarrow 1} & \theta^{(h)}_{1\leftarrow 2} & \cdots & \theta^{(h)}_{1\leftarrow d} \\ \theta^{(h)}_{2\leftarrow 1} & \theta^{(h)}_{2\leftarrow 2} & \cdots & \theta^{(h)}_{2\leftarrow d} \\ \vdots & \vdots & \ddots & \vdots \\ \theta^{(h)}_{d\leftarrow 1} & \theta^{(h)}_{d\leftarrow 2} & \cdots & \theta^{(h)}_{d\leftarrow d} \end{bmatrix}, \tag{7}$$

where each row of $C^{(h)}$ sums to $1/d$ and the matrix grand sum is 1. The i-th diagonal element of $C^{(h)}$, $\theta^{(h)}_{i\leftarrow i}$, measures the unilateral spillover (or loop) from variable i onto itself. We refer to this as the own variance share, $O^{(h)}_{i\leftarrow i}$. Meanwhile, the (i,j)th off-diagonal element of $C^{(h)}$, $\theta^{(h)}_{i\leftarrow j}$, measures the spillover from variable j to variable i. The spillover from the rest of the system to variable i is:

$$F^{(h)}_{i\leftarrow\bullet} = \sum_{j=1,j\neq i}^{d} \theta^{(h)}_{i\leftarrow j}, \tag{8}$$

while the spillover from the i-th variable to the rest of the system is given by:

$$T^{(h)}_{\bullet\leftarrow i} = \sum_{j=1,j\neq i}^{d} \theta^{(h)}_{j\leftarrow i}. \tag{9}$$

The total and net h-steps-ahead connectedness of variable i, $A^{(h)}_i$ and $N^{(h)}_i$, are defined as follows:

$$A^{(h)}_i = T^{(h)}_{\bullet\leftarrow i} + F^{(h)}_{i\leftarrow\bullet} \quad \text{and} \quad N^{(h)}_i = T^{(h)}_{\bullet\leftarrow i} - F^{(h)}_{i\leftarrow\bullet}. \tag{10}$$

The spillover index introduced by Diebold and Yilmaz (2009) can be obtained as:

$$S^{(h)} = \sum_{i=1}^{d} F^{(h)}_{i\leftarrow\bullet} \equiv \sum_{i=1}^{d} T^{(h)}_{\bullet\leftarrow i}. \tag{11}$$

The spillover measures defined above focus on pairwise spillovers among individual variables. Following Greenwood-Nimmo et al. (2021), spillovers among variable groups can be evaluated by means of block aggregation of the connectedness matrix (7). For illustrative purposes, suppose that we wish to evaluate the connectedness among the M currencies in the model having aggregated all four variables relating to each currency into M currency-level groups.

First, note that we may write:

$$C^{(h)} = \begin{bmatrix} B_{1\leftarrow 1} & B_{1\leftarrow 2} & \dots & B_{1\leftarrow M} \\ B_{2\leftarrow 1} & B_{2\leftarrow 2} & \dots & B_{2\leftarrow M} \\ \vdots & \vdots & \ddots & \vdots \\ B_{M\leftarrow 1} & B_{M\leftarrow 2} & \dots & B_{M\leftarrow M} \end{bmatrix}, \tag{12}$$

where:

$$B_{i\leftarrow j} = \begin{bmatrix} \theta^{(h)}_{r_i\leftarrow r_j} & \theta^{(h)}_{r_i\leftarrow v_j} & \theta^{(h)}_{r_i\leftarrow q_j} & \theta^{(h)}_{r_i\leftarrow k_j} \\ \theta^{(h)}_{v_i\leftarrow r_j} & \theta^{(h)}_{v_i\leftarrow v_j} & \theta^{(h)}_{v_i\leftarrow q_j} & \theta^{(h)}_{v_i\leftarrow k_j} \\ \theta^{(h)}_{q_i\leftarrow r_j} & \theta^{(h)}_{q_i\leftarrow v_j} & \theta^{(h)}_{q_i\leftarrow q_j} & \theta^{(h)}_{q_i\leftarrow k_j} \\ \theta^{(h)}_{k_i\leftarrow r_j} & \theta^{(h)}_{k_i\leftarrow v_j} & \theta^{(h)}_{k_i\leftarrow q_j} & \theta^{(h)}_{k_i\leftarrow k_j} \end{bmatrix},$$

for $i, j = 1, 2, \dots, M$, where the block $B_{i\leftarrow i}$ collects all of the local spillover effects for currency i (i.e., all spillovers occurring among the risk and return measures for currency i), while the block $B_{i\leftarrow j}$ collects all of the spillover effects from currency j to currency i (i.e., all of the spillovers affecting the risk and return measures for currency i that originate from the risk and return measures for currency j). The total within-currency spillover effect for currency i is as follows:

$$\mathcal{W}^{(h)}_{i\leftarrow i} = \iota_4' B_{i\leftarrow i}\iota_4, \tag{13}$$

where ι_4 is a 4×1 vector of ones. As such, $\mathcal{W}^{(h)}_{i\leftarrow i}$ measures the proportion of the h-steps-ahead systemwide FEV accounted for by spillovers among the variables in $\check{\boldsymbol{y}}_{it}$.[10] Meanwhile, the pairwise spillover from currency j to currency i can be measured by:

$$\mathcal{F}^{(h)}_{i\leftarrow j} = \iota_4' B_{i\leftarrow j}\iota_4. \tag{14}$$

It is straightforward to construct the aggregate spillover measures for currency i with respect

[10] It is straightforward to decompose these currency-level connectedness measures into own-variable effects (e.g., return-to-return spillovers) and cross-variable effects (e.g., variance-to-return spillovers) if desired. To see this, consider the within-currency connectedness of the i-th currency, $\mathcal{W}^{(h)}_{i\leftarrow i}$, which may be decomposed to separate the own-variable FEV contributions within-currency i, $\mathcal{O}^{(h)}_{i\leftarrow i}$, from the cross-variable effects, $\mathcal{C}^{(h)}_{i\leftarrow i}$, as follows:

$$\mathcal{O}^{(h)}_{i\leftarrow i} = \text{trace}\left(B^{(h)}_{i\leftarrow i}\right) \quad \text{and} \quad \mathcal{C}^{(h)}_{i\leftarrow i} = \mathcal{W}^{(h)}_{i\leftarrow i} - \mathcal{O}^{(h)}_{i\leftarrow i},$$

where $\mathcal{O}^{(h)}_{i\leftarrow i}$ is the total own-variable spillover effect within currency i and $\mathcal{C}^{(h)}_{i\leftarrow i}$ represents spillovers between the log-return, variance, skewness and kurtosis innovations for currency i.

to the other $M-1$ currencies as follows:

$$\mathcal{F}_{i\leftarrow\bullet}^{(h)} = \sum_{j=1,j\neq i}^{M} \iota_4' B_{i\leftarrow j}\iota_4, \tag{15}$$

$$\mathcal{T}_{\bullet\leftarrow i}^{(h)} = \sum_{j=1,j\neq i}^{M} \iota_4' B_{j\leftarrow i}\iota_4. \tag{16}$$

Given $\mathcal{F}_{i\leftarrow\bullet}^{(h)}$ and $\mathcal{T}_{\bullet\leftarrow i}^{(h)}$, the total and net connectedness of each currency can be easily computed as follows:

$$\mathcal{A}_i^{(h)} = \mathcal{T}_{\bullet\leftarrow i}^{h} + \mathcal{F}_{i\leftarrow\bullet}^{(h)} \quad \text{and} \quad \mathcal{N}_i^{(h)} = \mathcal{T}_{\bullet\leftarrow i}^{(h)} - \mathcal{F}_{i\leftarrow\bullet}^{(h)}, \tag{17}$$

where $\mathcal{A}_i^{(h)}$ measures the overall strength of currency i's linkages with the other currencies in the system and $\mathcal{N}_i^{(h)}$ reflects the role of currency i in the system as a net transmitter (receiver) if $\mathcal{N}_i^{(h)} > 0$ (if $\mathcal{N}_i^{(h)} < 0$). The aggregate spillover index at the currency-level is obtained as follows:

$$\mathcal{S}^{(h)} = \sum_{i=1}^{M} \mathcal{F}_{i\leftarrow\bullet}^{(h)} \equiv \sum_{i=1}^{M} \mathcal{T}_{\bullet\leftarrow i}^{(h)}. \tag{18}$$

As shown by Greenwood-Nimmo et al. (2021), the aggregation procedure described above can be modified to accommodate any desired block structure in the connectedness matrix, $C^{(h)}$.

5 Results

5.1 Full-Sample Network Statistics

Our first task is to select the forecast horizon used in construction of the GVD, h. Initial experimentation with $h = \{5, 10, 15\}$ reveals that the network is largely insensitive to the choice of forecast horizon, as we will shortly demonstrate in the context of rolling sample analysis. Therefore, we select $h = 10$ trading days, which is a common choice in the literature and matches the forecast horizon used by GNR.

To place our subsequent analysis of the interaction of DM and EM currencies in context, we first provide an overview of the structure and features of the global FX network. In Figure 2, we plot a disaggregate representation of the FX network over the full sample. The figure is presented in the form of a heatmap, where the depth of shading is proportional to the strength of the bilateral spillover effects. To facilitate interpretation of the heatmap, the variables in the model are gathered into moment groups, such that all of the returns appear first, followed by all of the variance innovations and so on. Within each moment group, currencies are ordered by DM/EM status first and then by alphabetical order of their ISO 4217 alpha codes. This ordering has no effect on the estimated spillover effects, because the GVD is order-invariant—it is purely a presentational choice. It does, however, draw attention to two key features of the network.

<<< Insert Figure 2 about here >>>

First, the strongest spillovers lie on the prime diagonal of the connectedness matrix, indicating a substantial role of own-variable information in the FEV decomposition. This is consistent with the existing FX networks estimated by Greenwood-Nimmo et al. (2016) and Huynh et al. (2020), for example. However, on aggregate, it is bilateral spillovers that are the dominant force in the network, accounting for 63.2% of systemwide FEV over the full sample period. The importance of bilateral spillovers reflects the aggregate behavior of FX investors, whose portfolio management decisions take account of differences in the risk-return profiles across currencies and whose actions introduce interdependencies across the return distributions of different currencies.

Second, if one imagines partitioning the full-sample connectedness matrix in Figure 2 into 4^2 blocks of dimension $M \times M$, then the four blocks on the prime diagonal contain the majority of strong bilateral spillovers in the system. This indicates that spillovers within moment groups (e.g., return-to-return spillovers, variance-to-variance spillovers etc.) are stronger than spillovers between moment groups (e.g., variance-to-return spillovers) on average. Taking volatility spillovers as an example, this suggests that a volatility surprise to one currency that changes its perceived level of uncertainty is likely to spill-over more strongly to volatility in other currencies (changing their perceived uncertainty) than to their returns or higher-order moments (reflecting changes in their perceived up/downside risk and tail risk). This is a natural finding, as each of the realized moments captures a different type of risk.

On a superficial level, this apparent block structure provides some support for the common practice of modeling return and risk spillovers separately in the empirical network literature (e.g., estimating separate VAR models for returns and volatilities, such that the network of return spillovers and the network of volatility spillovers are independent of one-another), as in the seminal equity market spillover analysis presented by Diebold and Yilmaz (2009). However, developing separate network models in this way amounts to the assumption that the spillover effects contained in the off-diagonal blocks of the connectedness matrix are negligible. This is clearly not the case in Figure 2, where strong spillovers arise between moment groups, especially between returns and skewness innovations and, to a lesser degree, between variance and kurtosis innovations. This reflects the interplay of return and risk at the heart of portfolio management.

Returning to the previous example of a volatility surprise to one currency, while it may spill-over to volatility more strongly than to other moments, that does not rule out substantial cross-moment effects. To illustrate the point, suppose that it is an adverse surprise that induces a subset of investors to rebalance their portfolios away from that currency to manage their exposure to volatility. Their divestments will put downward pressure on the exchange rate of the shocked currency, depressing its returns and potentially affecting its downside and tail risk. As the investors rebalance their portfolios, they will adjust their holdings of other currencies, generating cross-currency spillover effects. One may expect these cross-currency spillovers to be weaker than the within-currency spillovers, as the effect of the rebalancing will be spread across many currencies. This is what we see in practice. The diagonal patterns in the top right and bottom left triangles of the connectedness matrix indicate that cross-moment spillovers are most pronounced within currencies (e.g., between the return and the skewness innovation for the same currency) but the presence of faint off-diagonal blocks in the connectedness matrix indicates that cross-moment, cross-currency spillovers cannot be considered negligible—the elements of the $4^2 - 4 = 12$ off-diagonal blocks in Figure 2 account for 16.9% of systemwide FEV.[11]

Careful scrutiny of Figure 2 suggests that there may be distinct DM and EM blocks in the network—for example, it seems that the block of return-to-return spillovers in the upper left of the figure could be further divided into sub-blocks of bilateral spillovers among groups of DM and EM currency returns. To explore this phenomenon with greater clarity, we make use of the block-aggregation routine of Greenwood-Nimmo et al. (2021) to transform the full-sample disaggregate connectedness matrix in Figure 2 into a currency-level connectedness matrix of dimension $M \times M$, which is presented in Figure 3. By analogy to Figure 2, the currencies are ordered by DM/EM status first and by alphabetical order of their ISO 4217 alpha codes second. Note that Figure 3 is obtained from a simple additive transformation of the information contained in Figure 2 and that the approximating VAR model is the same in both cases, which implies that the two figures are directly comparable and that the quoted spillover effects are measured on the same scale.

<<< Insert Figure 3 about here >>>

[11]These findings show that there is value in modeling risk and return spillovers jointly and that failure to do so would represent a mis-specification of the approximating VAR model. Baruník et al. (2017) make a similar observation in their analysis of asymmetric FX connectedness based on realized semivariances, which leads them to estimate a single model combining positive and negative semivariances rather than separate models for each, as in their earlier work on equity market connectedness (Baruník et al., 2016). A corollary of this observation is that techniques for dimension reduction (in our case, the LASSO estimator) are necessary to provide a means to fit such high-dimensional models given the number of observations available for estimation, particularly in a rolling-sample setting. Similar concerns underpin the adoption of LASSO and elastic net regularization for the estimation of network models in Demirer et al. (2017) and Bostanci and Yilmaz (2020).

Three features of Figure 3 are noteworthy. First, the strong spillovers along the prime diagonal of the heatmap indicate that within-currency effects are strong. Note that within-currency effects include univariate loops (e.g., the loop from the USDAUD return onto itself), as well as spillovers among return and risk innovations for the same currency (e.g., the spillover from the USDAUD variance innovation to the USDAUD return). As discussed above, it is natural to see strong within-currency spillover effects, as they reflect the interplay of returns and higher-order moment risks that underpins the overall risk-return profile of a currency.

Second, even though within-currency effects account for a large proportion of the 10-days-ahead FEV, it is cross-currency spillovers that are the dominant force in the network as a whole, accounting for 58.5% of systemwide FEV over the full sample.[12] There is a notable group of strongly interconnected currencies including the European DM currencies as well as USDAUD, USDCAD and USDPLN. This is similar to the European block documented by Diebold and Yilmaz (2015). By contrast, the remaining currencies do not form an obvious group.[13] There are several currencies for which the within-currency effect exceeds the sum of inward spillovers from the system. This is the case for 5/8 EMs but for just 2/12 DMs. This provides an initial glimpse of the differing behavior of DM and EM currencies, as it suggests that DM currencies are more integrated within the FX network than EM currencies on average, perhaps due to their greater average liquidity. A similar finding is made by Do et al. (2016), who document stronger evidence of realized volatility and kurtosis spillovers among DMs than EMs.

Third, all but three of the EM currencies (USDMXN, USDPLN and USDZAR) exhibit weak inward and outward spillovers over the full sample period. With the exception of USDBRL, all of the weakly connected EM currencies are Asian. Some Asian DM currencies also exhibit weak inward and outward spillovers, notably USDHKD and USDKRW. The weak spillovers associated with Asian currencies may reflect the management of several of these currencies over our sample period (USDCNY, USDHKD and USDINR) or a lack of a clear Asian block in foreign exchange market liquidity. For example, using bid-ask spreads for the same currency pairs that we study, Olds et al. (2021) document a lack of comovement in Asian foreign exchange liquidity, although they find that common variation in major exchange rates is associated with common variation in foreign exchange market liquidity for the full sample of currency pairs. The weak

[12] Note that the currency-level spillover index will be lower than the disaggregate spillover index by definition if there are any non-zero spillovers among the return and risk measures for at least one currency in the network, as these within-currency cross-variable effects are treated as unilateral loops in the currency-level network but as bilateral spillovers in the disaggregate network.

[13] Applying Ward's minimum variance method for hierarchical cluster analysis allowing for 2-5 clusters reveals that the nine strongly interconnected currencies form a stable cluster that is selected irrespective of the number of clusters that we allow for. By contrast, as the number of clusters increases, the remaining currencies tend to be clustered in pairs. Allowing for 5 clusters, we obtain three pairs—USDNZD and USDTRY, USDKRW and USDINR, and USDBRL and USDRUB. Results of cluster analysis are available from the authors on request.

integration of Asian currencies also has implications for portfolio diversification, as it indicates that they are less exposed to risks coming from elsewhere in the network. Consequently, they may offer diversification benefits with respect to non-Asian currencies.

Further aggregation of the FX network by DM/EM status using the block-aggregation method of Greenwood-Nimmo et al. (2021) yields a 2×2 connectedness matrix, which reveals that bilateral spillovers among the DM and EM currency groups account for 24.5% of systemwide FEV. Furthermore, this exercise reveals that DM-to-EM spillovers exceed EM-to-DM spillovers by 2.7 percentage points, indicating that EM currencies as a group are net recipients of foreign shocks on average over the full sample.

To illuminate the degree to which each currency influences/is influenced by the rest of the global FX network and to explore the extent of the heterogeneity across currencies, we compute measures of influence and dependence at the currency level following Greenwood-Nimmo et al. (2021). The dependence of the ith currency is defined as $\mathcal{D}_i^{(h)} = \mathcal{F}_{i\leftarrow\bullet}^{(h)}/(\mathcal{F}_{i\leftarrow\bullet}^{(h)} + \mathcal{W}_{i\leftarrow i}^{(h)})$ and the influence of the ith currency as $\mathcal{I}_i^{(h)} = \mathcal{N}_i^{(h)}/(\mathcal{T}_{\bullet\leftarrow i}^{(h)} + \mathcal{F}_{i\leftarrow\bullet}^{(h)})$. Consequently, the dependence index takes values in the unit interval, with smaller (larger) values indicating that the ith currency is less (more) dependent on spillovers from other currencies. Meanwhile, the influence index takes values in the interval $[-1, 1]$, with values close to 1 signifying a highly influential currency that strongly influences other currencies in the FX network and values close to -1 signifying a currency that is strongly influenced by the behavior of other currencies.

The position of each currency in dependence-influence space over the full sample is plotted in Figure 4. First, note that USDEUR lies at the upper right extreme of Figure 4, with an influence and dependence scores of 0.18 and 0.79, respectively. This reflects the important informational role that the euro plays in the global FX network as well as its deep integration in the network. This is not surprising, given that the euro is the second-most traded global currency behind the US dollar.

<<< Insert Figure 4 about here >>>

At the other extreme, USDCNY and the USDHKD record the lowest external dependence and influence among the currencies in our sample, with values of 0.28 and -0.62 respectively for USDCNY and 0.14 and -0.48 for USDHKD. For both currencies, their managed adjustment limits their fluctuations to a narrow range, and therefore affects the extent of their external dependence. In addition, the low influence of the yuan may result in part from our use of the onshore USDCNY exchange rate, as opposed to the offshore USDCNH exchange rate.[14]

[14] The particular behavior of the USDHKD in our model may also be affected by Hong Kong's unique role in yuan trading. Hong Kong is the principal location for conversion between the onshore CNY and offshore CNH.

The remaining currencies in our sample can be roughly partitioned into two groups. First, there is a group of DM currencies and liquid EM currencies for which the dependence index is typically greater than 0.5 and the influence index is typically close to zero. Currencies in this group are well-integrated into the global FX network, with many forming part of the cluster documented above. The other group contains mostly EM currencies, all with dependence indices less than 0.5 and negative influence indices, often substantially so. This suggests that many EMs play a relatively weak informational role in the foreign exchange network, at least over the full sample. Their low dependence on the behavior of other currencies also suggests that they may offer diversification opportunities with respect to DM currencies, as they may be less susceptible to network shocks (Broadstock et al., 2022).

5.2 Rolling-Sample Network Statistics

Full-sample network analysis provides a static impression of the average interaction of DM and EM currencies over our sample but it does not illuminate how their interactions evolve over time; for this, we turn to rolling-sample analysis. As a first step, it is necessary to select the window length to be used in the rolling-sample exercises, w. In selecting the window length, we must balance two important considerations: (i) a longer window contains more information and will yield more precise estimates of the VAR parameters in each rolling sample; and (ii) a shorter window will allow for greater timeliness in our rolling-sample analysis. We proceed by comparing the network obtained using window lengths in the set $w = \{200, 250, 300\}$ trading days, as in GNR. In practice, we find that the spillover statistics obtained in each case are similar, so we proceed on the basis that $w = 250$ without loss of generality. A concise comparison of the spillover indices obtained from all pairwise combinations of $h = \{5, 10, 15\}$ and $w = \{200, 250, 300\}$ may be found in Appendix A.

We begin by inspecting the 10-days-ahead disaggregate and currency level spillover indices evaluated on a rolling-sample basis to develop intuition for the dynamic evolution of global FX connectedness. Figure 5 reveals that the two spillover indices exhibit marked time-variation and share similar dynamics—in particular, both show elevated spillover activity in periods of stress, including the GFC, the European debt crisis, the wake of the Brexit referendum and during the

Offshore demand for Chinese equities is an important driver of demand for the HKD, because the Shanghai Connect and Shenzen Connect programs allow overseas investors to trade eligible shares on the Shanghai and Shenzen stock exchanges subject to a daily quota. Prior to the establishment of this program, offshore trading in mainland Chinese stocks was largely prohibited. These trades are settled in CNY, with many offshore investors converting from a foreign currency to HKD or CNH and then to CNY. This implies that a significant source of demand for the HKD is driven by demand for the onshore CNY, generating spillovers between the two currencies (note that the bilateral spillovers between USDHDK and USDCNY are among the strongest spillovers affecting either currency in Figure 3).

COVID pandemic.[15] This finding is consistent with the results of Bubák et al. (2011) for EM currencies and GNR for DM currencies. In addition, elevated spillover activity in periods of stress has been widely documented in other asset classes, including equity and credit derivatives (e.g., Diebold and Yilmaz, 2009; Demirer et al., 2017; Greenwood-Nimmo et al., 2019; Bostanci and Yilmaz, 2020; Ando et al., 2022). Following GNR, a plausible explanation of this finding is that investors may rebalance their portfolios more frequently or more substantially in volatile states of the world, when risk appetite is low. Furthermore, in extreme states of the world where liquidity abruptly dries up, some investors may be forced to unwind positions on disadvantageous terms, as described in the crash risk literature (e.g., Brunnermeier et al., 2009; Rafferty, 2012).

<<< Insert Figure 5 about here >>>

Unlike most existing network models that only contain DM currencies (e.g., Greenwood-Nimmo et al., 2016; Huynh et al., 2020), we can investigate how the relative spillover between DM and EM currencies evolves over time and whether changes in the relative connectedness of these two groups contribute to the pattern of time-variation observed in Figure 5. Of particular interest in this context is the stylized fact that net capital flows from DMs to EMs are volatile and prone to reversal during periods of elevated uncertainty and reduced risk appetite (e.g., Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012; Fratzscher et al., 2018). Such changes in the nature of DM/EM capital flows may contribute to the elevated FX connectedness that we observe in times of stress, and would be expected to manifest as an increased relative role of bilateral DM/EM spillovers during volatile periods. To look for evidence of this phenomenon, we analyze the behavior of bidirectional spillovers among the DM and EM currency groups over rolling samples in Figure 6. In panel (a), we plot DM-to-EM and EM-to-DM spillovers over rolling samples. In panel (b), we show the proportion of the currency level spillover index that can be attributed to bilateral spillovers among DM and EM currencies. Lastly, in panel (c), we plot the net spillover from the DM currency group to the EM currency group.

<<< Insert Figure 6 about here >>>

[15] The fact that we observe such a strong impact of Brexit on the FX network reflects several factors. First, Brexit triggered a very large shock to FX markets. It caused the largest one-day fall in any of the world's four major currencies since the collapse of the Bretton Woods regime in 1971 (Costa et al., 2024). Brexit was followed by an increase in correlation among safe haven currencies and an increase volatility transmission in general (Dao et al., 2019), and led to a long-lived increase in FX volatility (Caporale et al., 2018). It also had a broad international economic impact that reached far beyond the FX market, propagating through diverse channels including its impact on banking losses (Abbassi and Bräuning, 2023) and exerting global impacts on listed firms in many countries (Hassan et al., 2024). In addition, Chuliá et al. (2018) note that the effect of large FX market shocks like Brexit may show up more in tail statistics than in volatility statistics. Consequently, the fact our model captures spillovers of higher-order moment risks, unlike most FX network models, may partly explain the large estimated effect of the Brexit shock.

The figure shows that the spillover in both directions between the DM and EM currency groups exhibits a similar pattern of time-variation to the currency spillover indices reported in Figure 5, with notable peaks in periods of financial market stress. The indicates that bidirectional information flow among DM and EM currencies increases in bad states of the world. Panel (b) reveals that the pattern of time-variation in the currency spillover index is strongly influenced by time-variation in the pattern of bilateral spillovers between the DM and EM currency groups, which change more abruptly on average than within-group (DM-to-DM and EM-to-EM) spillovers. The mean daily change in the bidirectional spillover between DM and EM currencies is 40% larger than the mean daily change in the within-group spillover, while the median daily change is 49% larger. Furthermore, the connectedness between DM and EM currencies adjusts more strongly than within-group connectedness in many historical periods of stress, meaning that risk and return spillovers among DMs and EMs assume a particular importance for FX investors at these times. It is plausible that this is related to the behavior of EM capital flows in times of stress discussed above. In addition, it indicates that models of the FX network that do not include both DM and EM currencies—including GNR and Huynh et al. (2020)—fail to capture an important source of time-varying FX connectedness, which limits their practical usefulness as tools for risk measurement and management, particularly in bad states of the world when such information may be most useful.

Panels (a) and (c) of Figure 6 reveal another interesting phenomenon. The net DM-to-EM spillover is typically positive, which reflects our full-sample finding that DM currencies play a more important informational role in the global FX network *on average*. However, there are several episodes during which the net DM-to-EM spillover drops toward zero or becomes negative, which implies that the information flow from EM-to-DM currencies becomes comparable to or even exceeds that from DM-to-EM currencies. The first of these episodes occurs in late 2007, during the GFC. The second is in 2010-11, which was a time of elevated sovereign risk in Europe. The third occurs in 2014, around the time of the imposition of sanctions against Russia for its annexation of the Crimea. The last corresponds to the emergence of COVID as a global pandemic. What these episodes have in common is that they are all periods of risk-off sentiment fueled by large adverse global shocks. This suggests that FX investors may respond more strongly than usual to EM news in adverse states of the world, perhaps due to their efforts to manage their exposure to EM risk at such times. We return to this point in Section 5.3.

Our model allows us to dig deeper into the different behavior of DM and EM currencies in the global FX network. Figure 7 shows how DM/EM spillovers are distributed across return and risk innovations. As in the full-sample results, the figure reveals that spillovers within moment groups (e.g., return-to-return spillovers, variance-to-variance spillovers etc.) are generally stronger than spillovers between moment groups (e.g., variance-to-return spillovers). Furthermore, the figure reveals substantial time-variation. For example, early in the sample, the stongest DM/EM spillovers occur among returns. By the time of the Brexit referendum, volatility-to-volatility spillovers are by far the strongest group, with the DM-to-EM spillover significantly exceeding the EM-to-DM spillover, indicating a net transmission of DM uncertainty onto EMs. The same is true during the COVID pandemic. Likewise, tail risk spillovers among DMs and EMs intensify in the last half of the sample, with DM-to-EM skewness and kurtosis spillovers coming to exceed their EM-to-DM counterparts during the COVID pandemic. The intensification of bidirectional risk spillovers among DMs and EMs in the last half of the sample suggests that diversification opportunities among DM and EM currencies may have diminished. In most of the panels of Figure 6, the DM-to-EM spillover exceeds the EM-to-DM spillover. However, this general result breaks down in the case of EM return spillovers onto the DM higher moment innovations, for which there are prolonged periods of negative net spillover with respect to EM returns in the first half of the sample. This suggests that the sensitivity of DM currency risk profiles to EM appreciations and depreciations has diminished in recent years.

<<< Insert Figure 7 about here >>>

Given the marked time-variation in DM/EM spillovers documented above, it is natural to ask whether the influence and dependence properties of the currencies in our sample also change over time. To investigate this issue, in Figure 8 we draw an arrow in influence-dependence space that shows the change in both influence and dependence over the 14 years from December 31, 2007 to December 31, 2021.[16] The results give rise to an interesting distinction. First, consider the DM currencies. Most experience little change in influence over this time but have become more externally dependent. There are two exceptions, both of them Asian currencies—USDKRW exhibits a substantial reduction in dependence, while USDHKD exhibits falling influence. Likewise, the EM currencies can be roughly partitioned into two groups. The USDINR, USDMXN, USDPLN and USDZAR exhibit similar behavior to the DMs in our sample. These are among the most liquid EM currencies and they are backed by relatively deep financial markets (see Olds et al., 2021, and the BIS triennial survey linked in footnote 3 on page 7). Meanwhile, among the remaining four EMs, only USDCNY records a modest increase in dependence and influence, but that is from a low starting point. The rest have become less externally dependent and less influential. The implication is that, while most DM currencies have become more

[16]That is, between 250-day rolling samples ending on December 31, 2007 and December 31, 2021.

integrated within the FX network over our sample period, many EM currencies have become less so, particularly those that have experienced instability over our sample period.

<<< Insert Figure 8 about here >>>

5.3 What Explains Net DM-to-EM Spillover Dynamics?

In light of the evidence presented above that bidirectional DM/EM spillovers peak during risk-off episodes and that net DM-to-EM spillovers tend to become less positive or even negative at the time of large adverse shocks, we now investigate whether bilateral DM/EM spillovers are related to international capital flows and the factors that drive them.

We start by conducting a graphical analysis of the net DM-to-EM spillover relative to EM capital flows. Portfolio equity and debt flows are typically recorded at quarterly frequency as part of the balance of payments statistics. The Institute of International Finance (IIF) maintains a capital flows tracker at monthly frequency, but no higher frequency data on EM portfolio flows is available. Consequently, in Figure 9, we plot the IIF tracker against end-of-month values of our DM/EM spillover statistics.[17] The figure reveals that net DM-to-EM spillovers covary weakly with EM capital flows in normal times (the correlation is 0.075) but that large capital outflows from EMs coincide with abrupt falls in the net DM-to-EM spillover, notably during the GFC and at the onset of the COVID pandemic. Recall from Figure 6(a) that, in both cases, bidirectional spillovers between DMs and EMs tend to intensify, but EM-to-DM spillovers rise faster than DM-to-EM spillovers.

<<< Insert Figure 9 about here >>>

While the low frequency of the capital flows data limits comparisons with our daily spillover statistics, the 'push vs. pull' literature on the determinants of EM capital flows draws attention to a range of higher frequency macroeconomic and financial indicators that may affect spillover activity (e.g., Calvo et al., 1993; Fernandez-Arias, 1996). Flows to a given EM are likely to depend on a range of domestic 'pull' factors, such as domestic interest rates, domestic growth prospects and the perceived stability of the domestic economy. In addition, capital flows to EMs as a group are affected by a range of external 'push' factors, including global uncertainty, global risk appetite, DM interest rates and DM growth prospects. Given that our interest here is on spillovers involving EMs as a group, we set aside market-specific pull factors and instead focus on common global push factors to provide higher-frequency insights into the evolution of DM/EM spillovers than is possible using data on capital flows directly. Our focus

[17] The results are comparable using period-average values as opposed to end-of-period values.

on international factors is supported by the results of Forbes and Warnock (2012), which indicate that domestic macroeconomic characteristics are less important in explaining extreme capital flows than global factors. We consider the following indicators of global macroeconomic and financial conditions:[18]

(i) The Chicago Board Options Exchange (CBOE) volatility index (VIX) is a forward-looking option-implied measure of volatility on the S&P 500. It is commonly interpreted as an 'investor fear gauge', with abrupt increases in the VIX being associated with elevated uncertainty and reduced investor risk appetite, both phenomena that are associated with capital outflow from EMs. In their analysis, Forbes and Warnock (2012) use the VXO (the predecessor of the VIX) to measure global risk due to its extended sample period.

(ii) The Treasury-Eurodollar (TED) spread is the spread between the 90-day USD London Interbank Offered Rate (LIBOR) and the 90-day US Treasury Bill yield. The TED spread measures liquidity in the interbank money market, which affects funding liquidity in general. Liquidity freezes may precipitate the forced unwinding of positions by FX investors, as discussed by Rafferty (2012).

(iii) The effective federal funds rate is a key benchmark interest rate both in the US and globally. Adjustments to the federal funds rate not only provide information on the state of the US economy but also affect the interest rates available on US assets and indirectly affect foreign interest rates due to monetary policy spillovers. In their analysis of risk and return spillovers among DMs, GNR show that the spillover index is inversely related to the federal funds rate, which implies that bilateral spillovers strengthen (weaken) as conditions in the US deteriorate (improve).

(iv) The US Dollar Index maintained by the Intercontinental Exchange (abbreviated DXY) is defined as a geometric weighted average of the value of the US dollar against a basket of six DM currencies, with the euro receiving a dominant weighting. An increase (decrease) in the value of the DXY signifies an appreciation (depreciation) of the US dollar relative to the basket of currencies. The DXY can be thought of as a proxy for the US dollar factor of Lustig et al. (2011).

[18] The gold price is sourced from Goldhub (`https://www.gold.org/goldhub/data/gold-prices`). The US-China tensions index is sourced from the Economic Policy Uncertainty website (`https://www.policyuncertainty.com/US_China_Tension.html`). The global financial stress index is sourced from the Office of Financial Research (`https://www.financialresearch.gov/financial-stress-index/`). All remaining series are retrieved from the Federal Reserve Economic Data Service (`https://fred.stlouisfed.org/`). All series are sampled daily apart from the US-China tensions index, which is only available at monthly frequency. To convert to daily frequency, we assume there is no change within each month and set the value for every day in a month equal to the quoted monthly value.

(v) Because the DXY excludes EM currencies, we also consider the Nominal Emerging Market Economies US Dollar Index published by the Board of Governors of the Federal Reserve System in its H.10 release. An increase (decrease) in the index value signifies an appreciation (depreciation) of the US dollar against the EM currency basket. Although the two exchange rate indices share a correlation of 0.90 over our sample, there are periods when their behavior differs appreciably, most recently during the COVID pandemic. Avdjiev et al. (2019) and Hofmann and Park (2020) show that the broad dollar index can be interpreted as an EM risk factor, with EM economies historically under-performing when the dollar is strong.

(vi) The slope of the US yield curve measured by the spread between the 10-year and 90-day US treasury yields conveys valuable information on the US macroeconomic outlook, including inflation expectations and output growth expectations. The US yield curve has also been shown to be predictive of future inflation and growth in EMs, especially those operating dollar pegs (e.g Mehl, 2009).

(vii) The daily news-based US economic policy uncertainty (EPU) index proposed by Baker et al. (2016) provides a timely indicator of policy-related economic uncertainty, increases in which are associated with depressed economic activity in the US and beyond.

(viii) The gold price tends to rise during periods of uncertainty, as investors treat gold as a safe-haven asset due to its intrinsic value and limited supply. Consequently, in periods of uncertainty, investors may reduce their FX exposures and increase their gold holdings. Gold has been shown to offer a hedge and a safe haven for many DM assets, but not necessarily for EM assets (e.g., Baur and McDermott, 2010; Bekiros et al., 2017).

(ix) The Office of Financial Research global financial stress index captures systemic financial stress at a global level by combining information on 33 indicators of financial market conditions using a dynamic factor model. Shim and Shin (2021) show that financial stress is associated with EM capital outflows.

(x) The US–China tensions (UCT) index developed by Rogers et al. (2024) is a text-based index of tension between the world's two largest economies. Periods of elevated tension have been associated with retrenchments of US corporate investment and adaptations of global supply chains. Of particular important in our context is the ability of the index to provide a nuanced characterization of the US–China trade-war beginning in 2018.

In Figure 10, the net DM-to-EM spillover estimated over 250-day rolling-samples is plotted against each of these international factors in turn, while the results of auxiliary regressions of the net DM-to-EM spillover on the international factors, both individually and as a group, are reported in Table 2.[19] Note that the net DM-to-EM spillover and each of the international factors are standardized to allow for straightforward comparisons that are not impeded by the large scale differences in the raw data. Note also that we control for the COVID period in our regressions by including an indicator variable that takes the value one from 2020-01-30 (when the World Health Organization declared COVID a Public Health Emergency of International Concern) until the end of our sample on 2021-12-31, and zero otherwise.

<<< Insert Figure 10 and Table 2 about here >>>

Visual inspection of Figure 10 reveals that abrupt changes in the VIX, the TED spread, the EPU index and the financial stress index tend to coincide with abrupt reductions in net DM-to-EM spillovers, which signify an increase in the relative role of EM-to-DM spillovers in the FX network. The remaining international factors plotted in Figure 10 display more gradual comovements with net DM-to-EM spillovers.

In Table 2, a positive (negative) coefficient estimate indicates that, all else equal, an increase in the value of a given international factor is associated with a relative decrease (increase) in the informational role of EMs compared to DMs. In the multiple regression model, each of the explanatory variables is statistically significant, with all but the TED spread being significant at the 1% level. This is compelling evidence that the balance of spillovers among DM and EM currencies is contemporaneously influenced by global macroeconomic and financial conditions that are known to affect EM capital flows. The sign of the parameter estimates in the multiple regression model provides a simple means to classify our explanatory variables into two groups—those associated with an increase in the relative role of EM-to-DM spillovers (negative sign) and those associated with an increased relative role of DM-to-EM spillovers (positive sign). For brevity, we will simply refer to EM-favoring and DM-favoring factors, respectively.

The EM-favoring group comprises the VIX, the DXY dollar index, the EPU index and the UCT index. The VIX and the EPU index capture different aspects of uncertainty. The link between investor fear captured by the VIX and EM capital outflows is well-established, while EM capital flows have been shown to be sensitive to US economic policy uncertainty (see Gauvin et al., 2014) and to DM uncertainty in general (see Bhattarai et al., 2020). Our results suggest that the FX market becomes relatively more sensitive to EM shocks during periods

[19] Estimation results using the net DM-to-EM spillover obtained with the window length set to both 200 and 300 trading days are presented in Appendix A. The sign and pattern of significance of the estimated parameters are robust across each specification. We also verify that our results are robust to lagging the explanatory variables by one period, which mitigates concerns over endogeneity. These results are available from the authors on request.

of uncertainty. In a similar vein, the UCT index captures friction among the world's largest economies. Since the start of the US-China trade war in 2018, the potential for these tensions to result in punitive measures like tariffs has become apparent. Consequently, periods of escalating US-China tension create uncertainty about global supply chains, weakening investor perceptions of the growth prospects of many export-dependent EMs.[20] Such escalations may encourage FX investors to pay greater attention to their EM exposures, increasing the sensitivity to EM news.

To interpret the coefficient estimate on the DXY, one must recall that we control for the trade-weighted EM exchange rate, and vice-versa. Consequently, it is helpful to discuss these two coefficients together. The negative coefficient estimate on the DXY should be interpreted as evidence that a depreciation of DMs relative to EMs is EM-favoring. This is likely to reflect FX investors increasing their EM exposures when EM currencies appreciate as a group, which provides a natural explanation for an enhanced informational role of EM currencies. Meanwhile, in our univariate regressions, the EM dollar index is the single variable with the highest explanatory power, accounting for more than 20% of the variance in net DM-to-EM spillovers. The broad USD exchange rate has been identified as an EM risk factor, with broad-based USD appreciations being linked to reduced investment in EMs and the under-performance of EM economies (e.g., Avdjiev et al., 2019; Hofmann and Park, 2020).

Besides the EM Dollar Index, the DM-favoring group comprises the TED spread, the effective federal funds rate, the slope of the US yield curve, the gold price and the financial stress index. The first three of these variables all convey information on aspects of liquidity. The positive coefficients on the federal funds rate and yield curve slope indicate that tighter US monetary policy and a steeper yield curve are DM-favoring. Given the linearity of the model, an equivalent interpretation is that reductions in the federal funds rate and a flattening of the yield curve are EM-favoring. This suggests that a role for search-for-yield among FX investors driven by low US interest rates (which tend to correlate with low interest rates in other DMs) promoting investment flows into EM assets offering higher returns.[21] Meanwhile, holding all else constant, increases in the TED spread that signify tightening liquidity conditions are associated with a greater relative role of DM-to-EM spillovers in the global FX network.[22] Liquidity constraints associated with spikes in the TED spread have been highlighted as a cause of abrupt currency swings in the literature on FX crash risk (e.g., Brunnermeier et al., 2009; Rafferty, 2012). In

[20]See https://www.ft.com/content/da45d9b6-7c74-11e9-81d2-f785092ab560 for contemporary media coverage on this point in the context of the US-China trade war.

[21]See Lim and Mohapatra (2016), Ho et al. (2018) and Kolasa and Wesołowski (2020) for a related discussion on quantitative easing and capital flows.

[22]Although the net DM-to-EM spillover is negatively correlated with the TED spread (as seen in Figure 10(b) and in the simple regression reported in Table 2), the relationship between the two is positive after controlling for the other variables.

particular, liquidity crunches may precipitate coordinated crashes among carry trade currency pairs. Faced with a liquidity shortage, FX investors may be obliged to unwind carry trades on unfavorable terms, precipitating a depreciation of the investment currency relative to the funding currency that further squeezes other investors engaged in similar trades. Our evidence indicates that it is DM currencies that play the more important role in transmitting the effects of liquidity disruptions around the FX network, which is consistent with the observation that the most well-known currency carry trades involve DM currencies on both the funding and investment legs, such as the well-known JPY–AUD carry trade.[23]

The positive coefficient estimates on the gold price and the financial stability index reflect the tendency for investors to withdraw from EM assets during periods of instability. Gold is widely used as a safe haven by investors, which tends to increase the gold price in bad states of the world, when the willingness of investors to hold EM positions declines. Likewise, periods of global financial stress correlate with EM outflows.[24] In periods of stress, many investors will retreat to DM assets that are perceived to be relatively safe, increasing the informational role of DM currencies in the FX network.

Overall, the evidence reported in Table 2 indicates that international factors that are known to affect EM capital flows can explain more than two-fifths of the variance of net DM-to-EM spillovers over our sample period ($\bar{R}^2 = 0.426$). This is remarkably high given that we focus only on international factors and do not consider any currency-specific variables. Knowledge of these explanatory factors can help FX investors to better understand the dynamic evolution of global FX connectedness and may contribute to improved risk management, particularly to the extent that properly characterizing higher-moment risks is critical for the estimation of quantities such as value-at-risk (e.g., Jondeau and Rockinger, 2000). It may also be useful for national policymakers seeking to better understand FX fluctuations and related issues including capital flow dynamics.

[23] A popular method of assessing the attractiveness of a carry trade is to consider the carry-to-risk ratio, which is the ratio of the interest rate differential between a pair of currencies to the implied volatility of that currency pair. The higher the carry-to-risk ratio, the more attractive the carry trade. In practice, over our sample period, many FX carry trades involved CHF, JPY or USD funding and targeted DM investment currencies, most famously the AUD. These investment currencies tend to exhibit lower implied volatility relative to popular funding currencies when compared against their EM counterparts. As a result, EM currencies may be viewed as less attractive investment options for currency carry traders, which offers a plausible explanation for the relationship between the TED spread and the net DM-to-EM spillover that we estimate.

[24] The positive estimated coefficient on the COVID indicator has a similar interpretation, as the Independent Evaluation Office of the IMF's appraisal of August 2020 notes that the COVID pandemic triggered 'unusually large portfolio outflows' from EMs (Batini, 2020).

6 Conclusion

We study the interaction between FX returns and the innovations in realized volatility, skewness and kurtosis for a large group of 12 DM currencies and 8 EM currencies over the period July 2006 to December 2021. Our work combines several recent innovations in the analysis of financial networks, including the aggregation-robust generalization of the DY connectedness methodology proposed by Greenwood-Nimmo et al. (2021) and the use of a shrinkage and selection estimator following Nicholson et al. (2017), which mitigates the overfitting problem in the estimation of large VAR models like ours and facilitates estimation in a rolling-sample setting in which each rolling sample is relatively small given the dimension of the model to be estimated.

We make several important findings. First, we document strong spillovers among returns and risk measures. Over the full-sample, we find that 16.9% of systemwide FEV is due to cross-moment spillovers, which highlights the importance of modeling returns and higher-order risk measures jointly rather than separately, as is common in the empirical network literature (e.g Diebold and Yilmaz, 2009). Second, we document strong bilateral spillovers between DM and EM currencies. Over the full sample, bilateral spillovers among DMs and EMs account for 24.5% of systemwide FEV. Third, we demonstrate a clear difference in the behavior of DM and EM currencies over the full sample. DM currencies tend to be more influential than their EM counterparts in the sense that they create stronger outward spillovers. In addition, DM currencies are more integrated within the FX network in the sense that a greater proportion of their FEV is explained by inward spillovers than is the case for EM currencies. On average, DM-to-EM spillovers exceed EM-to-DM spillovers by 2.7 percentage points, indicating that EM currencies as a group are net recipients of DM currency shocks on average over the full sample.

In rolling-sample analysis, we show that currency markets become more strongly interconnected during periods of stress, in keeping with the results of Bubák et al. (2011) for EM currencies and GNR for DM currencies. Furthermore, we show that the time-varying pattern of spillover activity is driven more by bilateral spillovers among DMs and EMs than by DM-to-DM and EM-to-EM spillovers, with the former evolving more rapidly than the latter. A plausible explanation for this phenomenon lies in the stylized fact that net capital flows from DMs to EMs are volatile and prone to reversal during periods of elevated uncertainty and reduced risk appetite (e.g., Forbes and Warnock, 2012, and the references therein). This suggests that investors rebalancing away from EMs may contribute to the elevated FX connectedness that we observe in times of stress. We provide indirect evidence of this phenomenon via an auxiliary regression exercise, which reveals that a set of global push factors that are believed to drive capital flows to EMs can explain more than two-fifths of variation in the net DM-to-EM spillover. To the best of our knowledge, ours is the first study to provide statistical evidence on the linkage between bilateral DM/EM spillover activity and the factors that drive capital flows between DMs and EMs and adds to the evidence of a link between FX connectedness and trade policy uncertainty put forth by Huynh et al. (2020).

We conclude by highlighting two fruitful avenues for continuing research. First, our results indicate that aggregate FX spillover activity is counter-cyclical, rising in bad states of the world and when US economic performance deteriorates. The development of theoretical models that can explain this behavior would be welcome. Second, in recent research, Broadstock et al. (2022) propose the notion of the minimum connectedness portfolio, or MCoP. The idea is that, by determining portfolio weights in a manner that minimizes connectedness across assets, one may construct a portfolio with reduced sensitivity to network shocks. In their study on green bonds, Broadstock et al. find that the MCoP achieves a higher Sharpe ratio than the minimum variance, minimum correlation or risk-parity portfolios. Of particular relevance in our context, He and Hamori (2024) provide evidence from the cryptocurrency market that minimum connectedness portfolios accounting for higher-order moment spillovers outperform a volatility-based MCoP. We look forward to future research that combines these insights in the context of higher-order moment FX network models such as ours.

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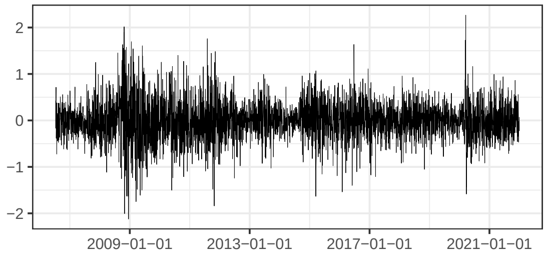
	Return			Realized Volatility			Realized Skewness			Realized Kurtosis		
	Mean	Med.	S.D.	Mean	Med.	S.D.	Mean	Med.	S.D.	Mean	Med.	S.D.
DM Currencies												
USDAUD	-0.004	-0.031	0.784	10.226	8.774	6.271	-0.022	0.021	1.587	10.392	5.486	15.316
USDCAD	0.003	-0.003	0.564	7.432	6.637	3.271	-0.056	0.009	1.586	10.676	6.023	15.017
USDCHF	-0.008	0.001	0.586	7.650	6.873	3.334	-0.041	-0.020	1.258	9.436	6.395	9.643
USDEUR	0.001	-0.001	0.560	7.147	6.518	3.150	-0.020	0.013	1.388	10.182	6.770	10.562
USDGBP	0.002	0.001	0.572	7.528	6.795	3.480	-0.013	0.001	1.519	10.803	6.686	12.747
USDHKD	0.000	0.000	0.035	0.476	0.406	0.303	-0.064	-0.023	1.045	11.294	9.042	7.866
USDJPY	0.006	0.008	0.591	7.358	6.561	3.708	-0.022	-0.026	1.447	10.166	6.148	12.596
USDKRW	-0.001	0.000	0.609	7.285	6.118	5.031	-0.174	-0.027	4.592	41.477	18.246	51.707
USDNOK	0.007	-0.006	0.784	10.287	9.241	4.598	-0.036	0.016	1.367	9.807	6.311	12.120
USDNZD	-0.009	-0.025	0.801	11.184	9.834	6.165	-0.017	-0.005	1.421	9.523	5.434	13.119
USDSEK	0.006	-0.006	0.735	9.553	8.439	4.202	-0.036	-0.010	1.317	9.664	6.296	10.803
USDSGD	-0.004	-0.013	0.334	4.402	4.049	1.711	0.007	0.028	0.975	7.700	5.655	6.750
EM Currencies												
USDBRL	0.017	0.000	1.038	12.833	11.436	6.557	-0.223	-0.112	3.126	29.205	17.771	28.199
USDCNY	-0.005	0.000	0.163	1.874	1.661	1.142	-0.293	-0.105	4.821	50.821	34.373	44.537
USDINR	0.014	0.000	0.449	7.365	5.997	4.428	1.446	0.847	4.286	50.240	35.024	44.785
USDMXN	0.017	-0.014	0.785	9.740	8.602	5.874	-0.097	-0.055	1.275	10.134	7.084	10.655
USDPLN	0.002	-0.010	0.867	10.686	9.163	5.475	-0.033	-0.012	1.105	8.771	6.461	7.936
USDRUB	0.018	0.000	0.881	9.867	7.907	7.120	-0.012	-0.041	2.083	15.758	8.786	21.765
USDTRY	0.054	0.011	0.984	11.657	10.038	7.706	-0.033	-0.009	1.488	11.630	7.512	13.970
USDZAR	0.013	-0.040	1.059	14.506	13.180	5.869	-0.053	-0.045	1.036	8.779	6.772	7.270

Table 1: Descriptive Statistics

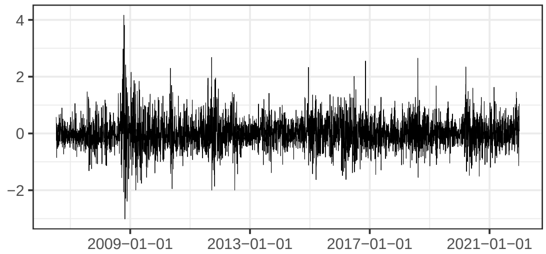
	Dependent variable: Net DM-to-EM Spillover											
Constant	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	0.000	−0.000	−0.150***	−0.113***
	(0.016)	(0.017)	(0.017)	(0.015)	(0.015)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.014)	(0.015)
VIX	−0.125***											−0.590***
	(0.012)											(0.029)
TED Spread		−0.084***										0.052*
		(0.012)										(0.029)
Federal Funds Rate			0.018									0.231***
			(0.012)									(0.040)
DXY Dollar Index				0.358***								−0.356***
				(0.014)								(0.043)
EM Dollar Index					0.475***							1.140***
					(0.018)							(0.048)
Slope of US YC						−0.268***						0.261***
						(0.013)						(0.042)
EPU Index							−0.071***					−0.169***
							(0.015)					(0.020)
Gold Price								0.209***				0.246***
								(0.018)				(0.034)
Financial Stress									−0.165***			0.588***
									(0.014)			(0.041)
US-China Tensions										0.206***		−0.322***
										(0.026)		(0.025)
COVID Indicator											1.128***	0.849***
											(0.074)	(0.089)
Adj. R-squared	0.015	0.007	0.000	0.128	0.225	0.072	0.005	0.043	0.027	0.042	0.147	0.426

Notes: Heteroskedasticity and autocorrelation robust standard errors are reported in brackets beneath each parameter estimate. Statistical significance at the 10%, 5% and 1% significance level is denoted by *, ** and ***, respectively. All variables aside from the COVID indicator are standardized to maintain comparability with Figure 10 and to prevent scale differences from hampering comparisons across coefficients.

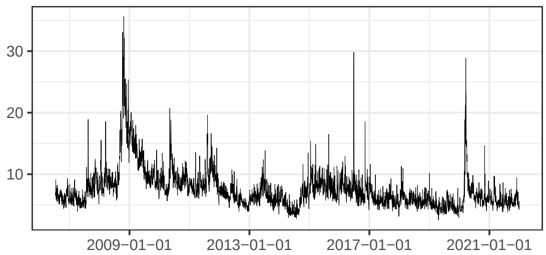
Table 2: Relations among the Net DM-to-EM Spillover and Global Push Factors



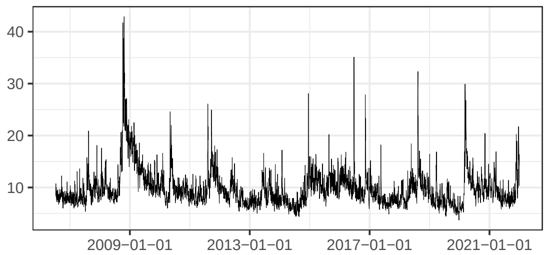
(a) Average DM return



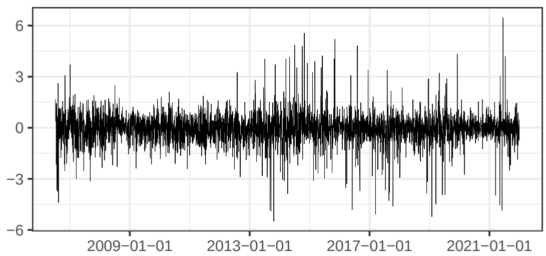
(b) Average EM return



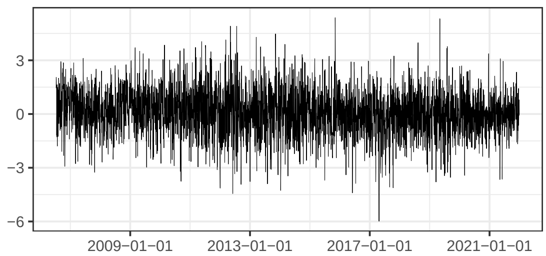
(c) Average DM volatility



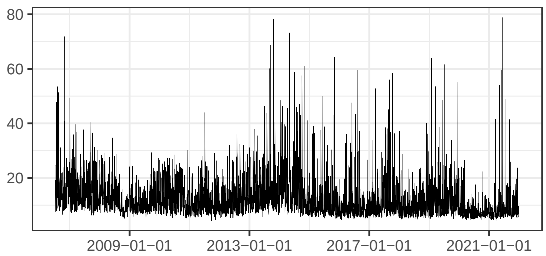
(d) Average EM volatility



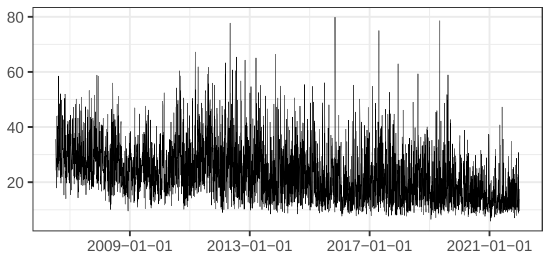
(e) Average DM skewness



(f) Average EM skewness

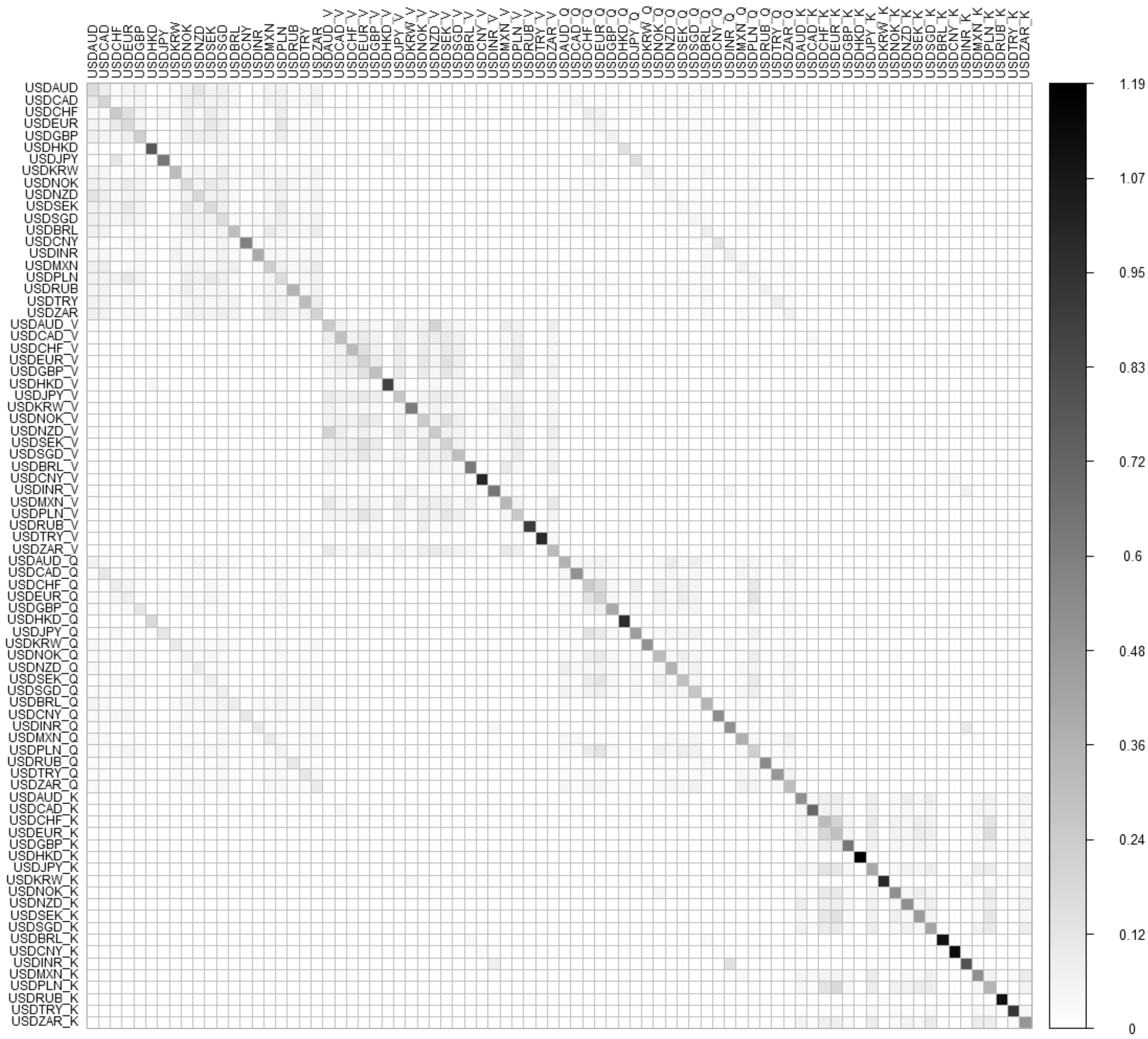


(g) Average DM kurtosis



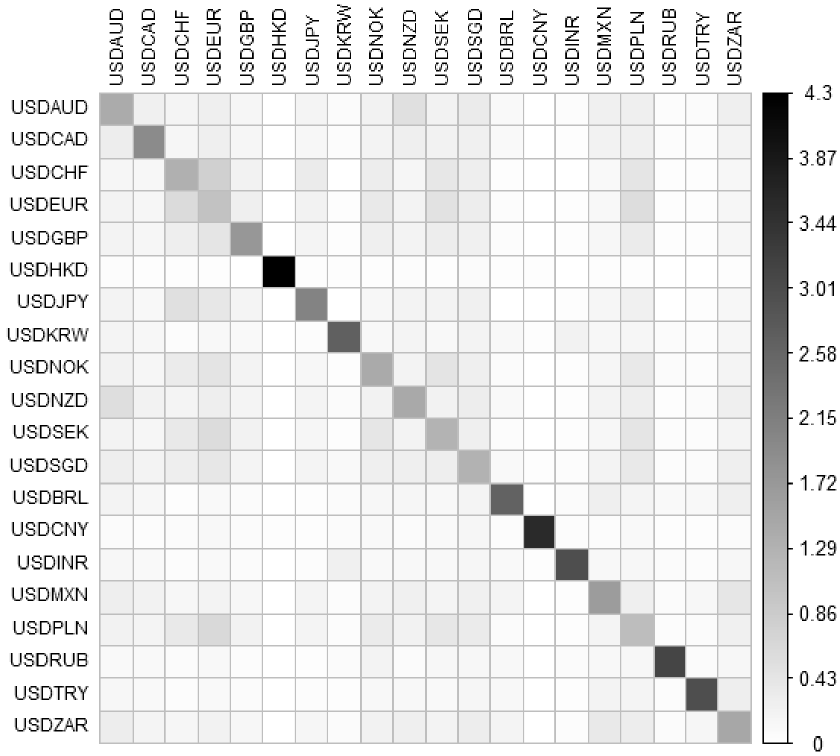
(h) Average EM kurtosis

Figure 1: Average Behavior of Returns and Risk Measures for DM and EM Currencies



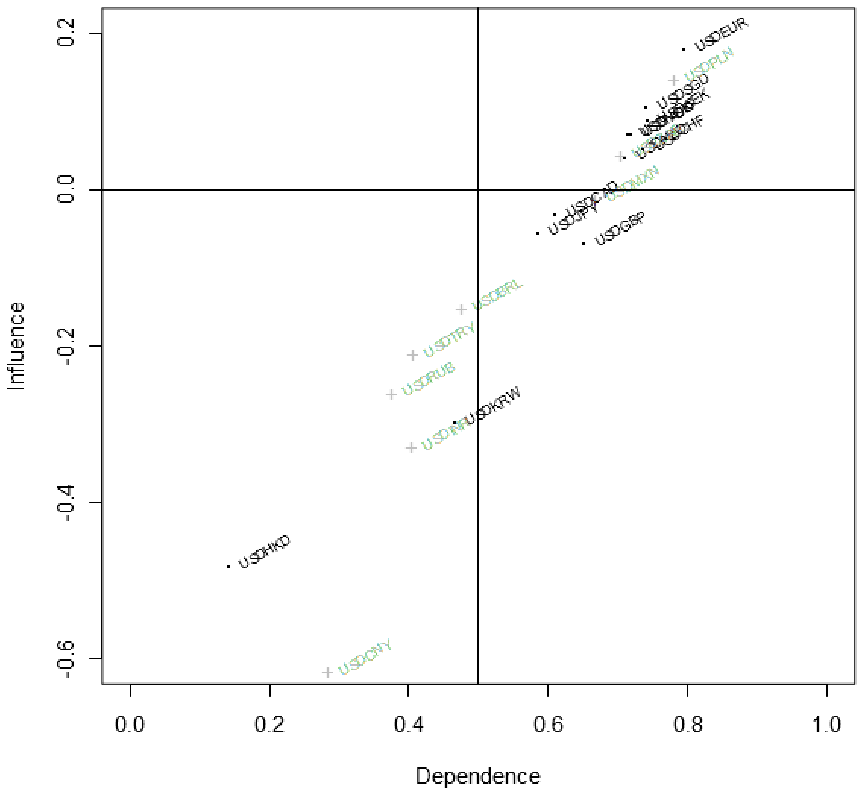
NOTES: The connectedness matrix is obtained by estimation over the full sample using a forecast horizon of 10 trading days. Variable names are abbreviated as follows: for currency XXX, USDXXX is the log-return, USDXXX_V is the realized variance innovation, USDXXX_Q is the realized skewness innovation and USDXXX_K is the realized kurtosis innovation. The depth of shading is proportional the strength of the spillover effect.

Figure 2: Disaggregate Connectedness over the Full Sample



NOTES: The currency connectedness matrix is obtained by block aggregation of the 10-days-ahead connectedness matrix evaluated over the full sample. The depth of shading is proportional to the strength of the spillover effect.

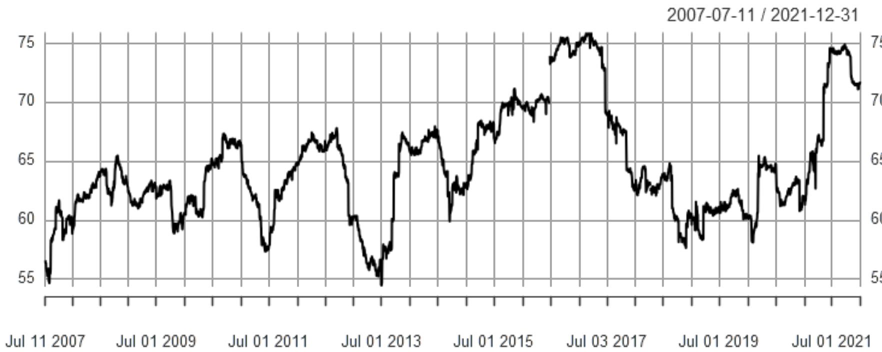
Figure 3: Connectedness among Currencies over the Full Sample



NOTES: The dependence of the ith currency is computed as $\mathcal{D}_i^{(h)} = \mathcal{F}_{i\leftarrow\bullet}^{(h)}/(\mathcal{F}_{i\leftarrow\bullet}^{(h)} + \mathcal{W}_{i\leftarrow i}^{(h)})$, while the influence of the ith currency is computed as $\mathcal{I}_i^{(h)} = \mathcal{N}_i^{(h)}/(\mathcal{T}_{\bullet\leftarrow i}^{(h)} + \mathcal{F}_{i\leftarrow\bullet}^{(h)})$. Both are constructed using a forecast horizon of 10 trading days over the full sample. DM currencies are marked with a black dot and EM currencies with a gray cross.

Figure 4: Influence and Dependence of Currencies over the Full Sample

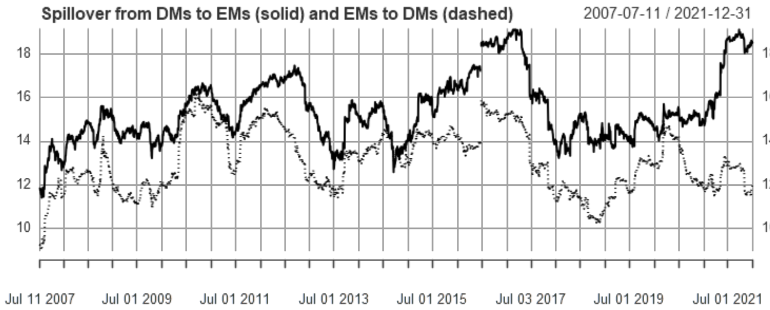
(a) Disaggregate spillover index



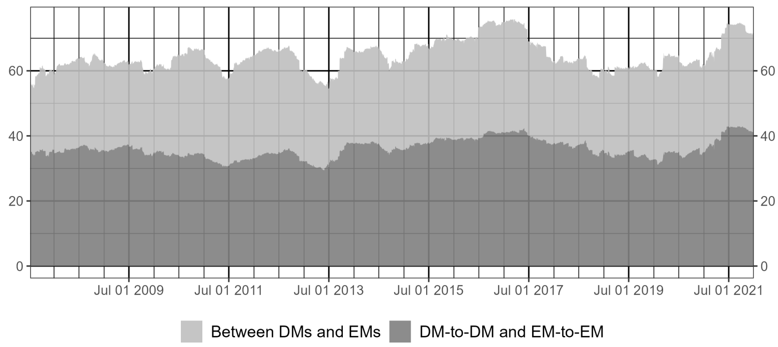
(b) Currency spillover index

Notes: Panel (a) reports the rolling sample spillover index computed from the disaggregate connectedness matrix, while panel (b) reports the corresponding spillover index computed from the currency connectedness matrix. In both cases, the forecast horizon is 10 trading days and the window length is 250 trading days. The dates reported on the horizontal axis relate to the end date of each rolling sample. The unit of measurement is percent. 2 out of 3,647 rolling samples yield unstable solves of the VAR model and are therefore excluded from the analysis, which results in some discontinuities in the time series plots.

Figure 5: Connectedness among Currencies over 250-day Rolling Samples



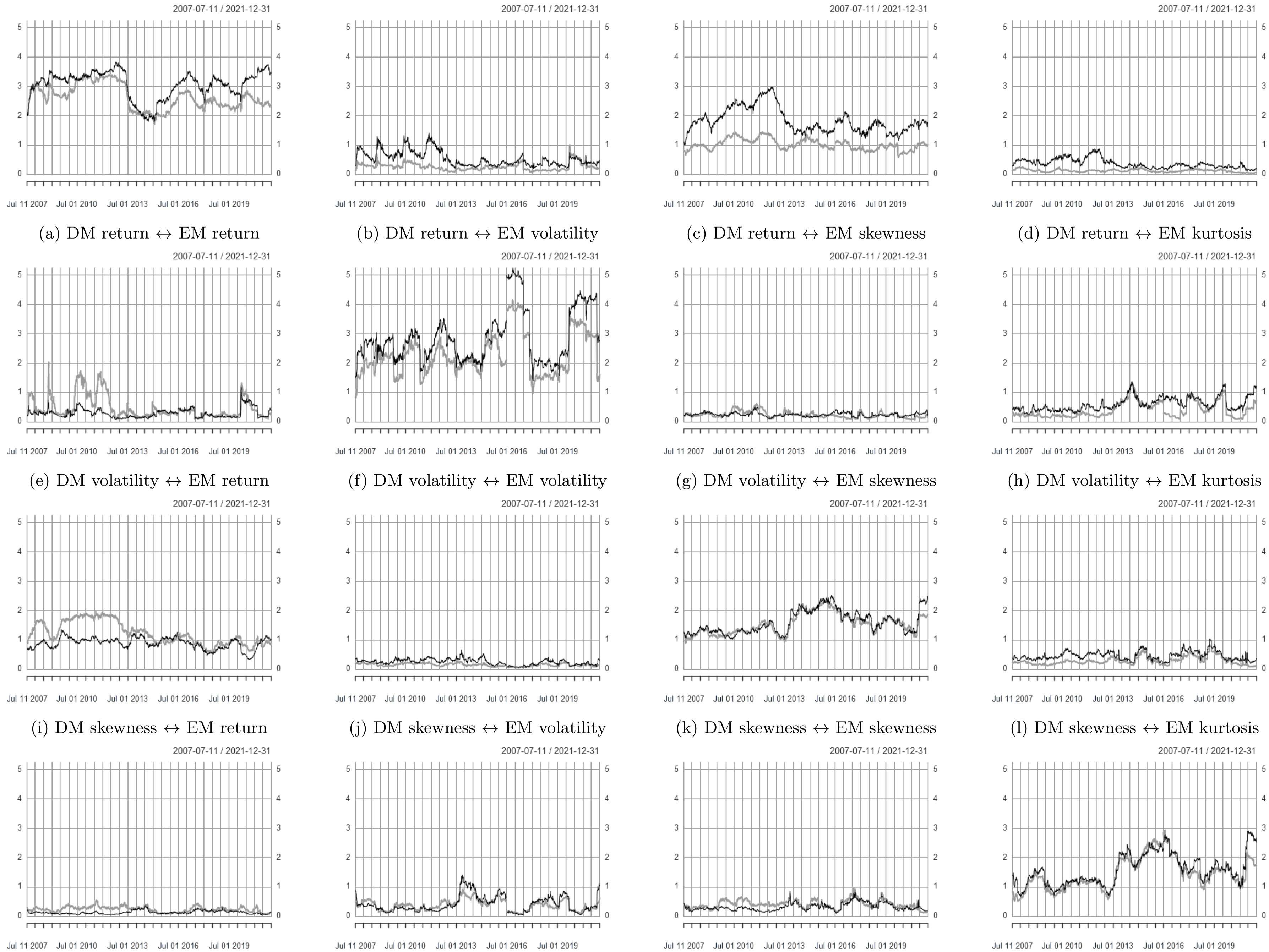
(a) Bidirectional Spillovers between DM and EM Currencies



(b) Total DM/EM Spillovers as a Proportion of Bilateral Spillovers among Currencies

(c) Net Spillover from DM to EM Currencies

Figure 6: Connectedness among DM and EM Currencies over 250-day Rolling Samples



(a) DM return ↔ EM return

(b) DM return ↔ EM volatility

(c) DM return ↔ EM skewness

(d) DM return ↔ EM kurtosis

(e) DM volatility ↔ EM return

(f) DM volatility ↔ EM volatility

(g) DM volatility ↔ EM skewness

(h) DM volatility ↔ EM kurtosis

(i) DM skewness ↔ EM return

(j) DM skewness ↔ EM volatility

(k) DM skewness ↔ EM skewness

(l) DM skewness ↔ EM kurtosis

(m) DM kurtosis ↔ EM return

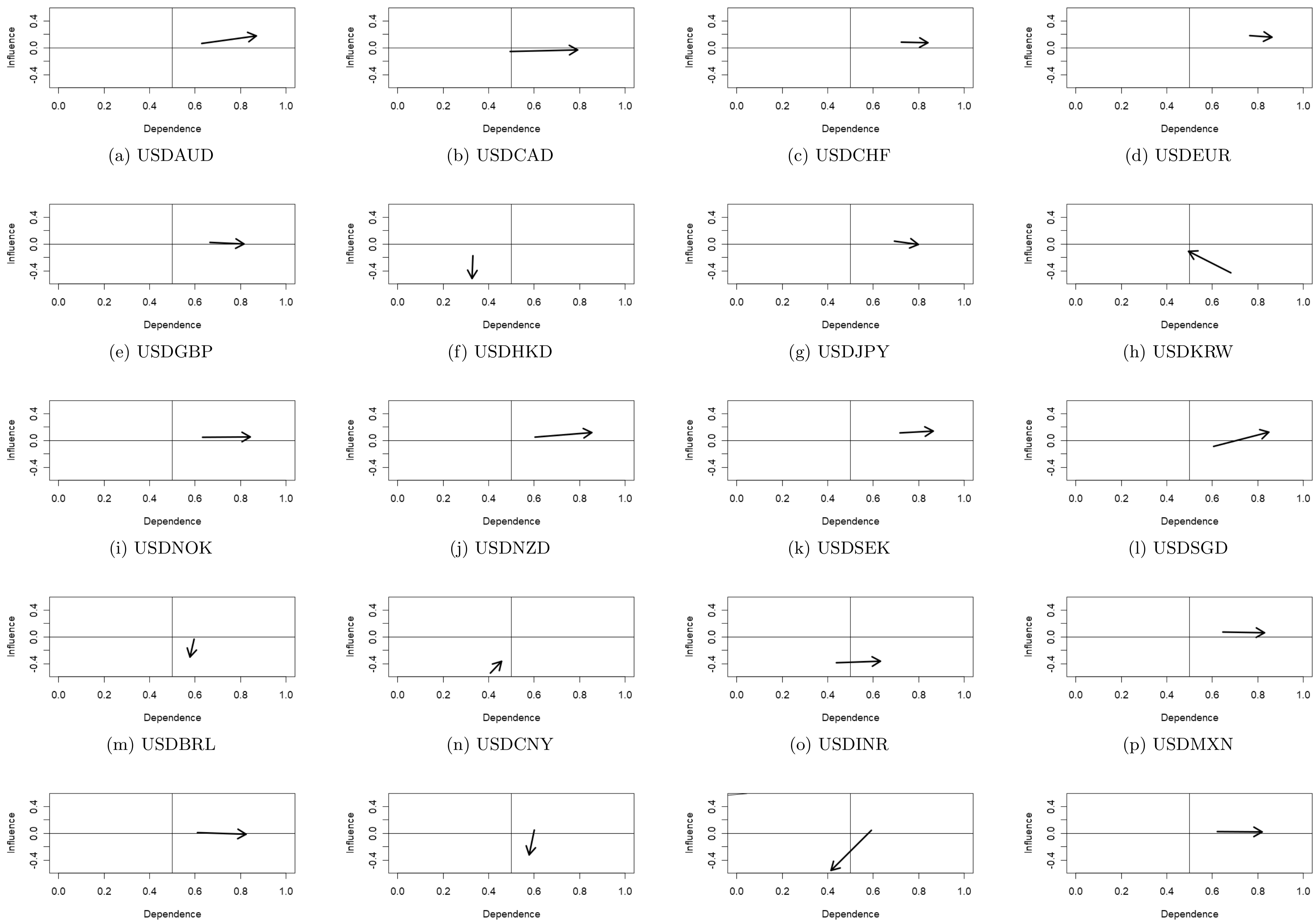
(n) DM kurtosis ↔ EM volatility

(o) DM kurtosis ↔ EM skewness

(p) DM kurtosis ↔ EM kurtosis

NOTES: In each panel, the DM-to-EM spillover is shown as a black line and the EM-to-DM spillover is shown as a gray line. The forecast horizon is 10 trading days and the window length is 250 trading days. The dates reported on the horizontal axis relate to the end date of each rolling sample. The unit of measurement is percent. 2 out of 3,647 rolling samples yield unstable solves of the VAR model and are therefore excluded from the analysis, which results in some discontinuities in the time series plots.

Figure 7: Breakdown of DM-to-EM and EM-to-DM Spillovers by Moment



(a) USDAUD (b) USDCAD (c) USDCHF (d) USDEUR

(e) USDGBP (f) USDHKD (g) USDJPY (h) USDKRW

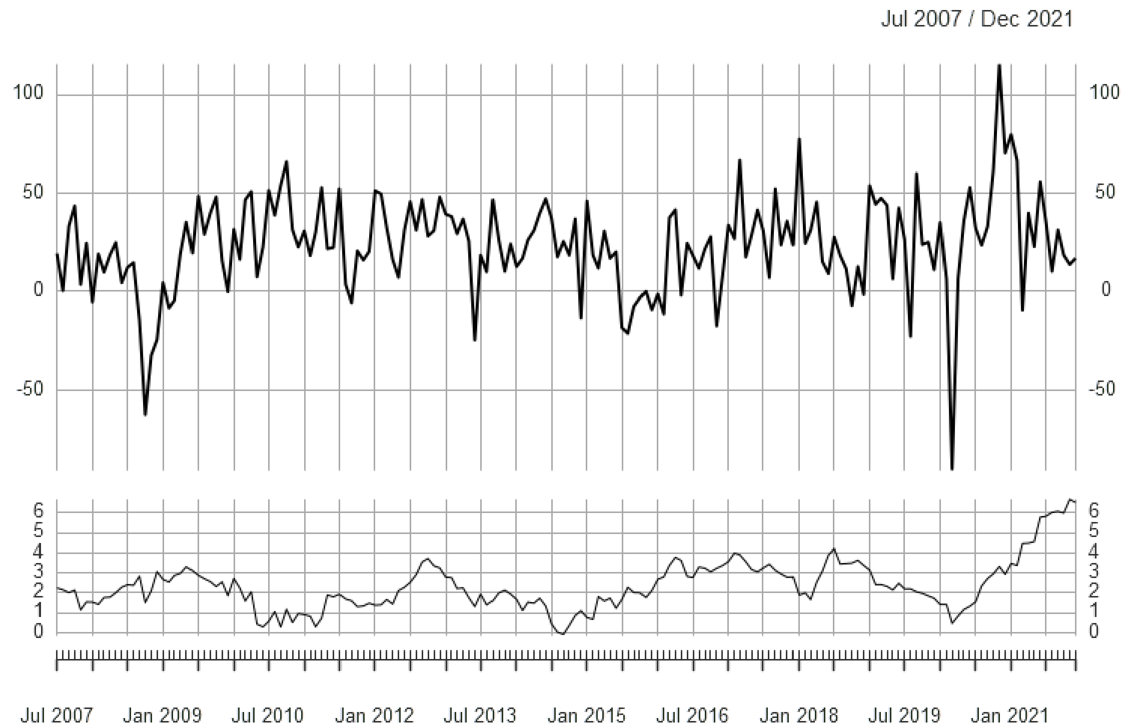
(i) USDNOK (j) USDNZD (k) USDSEK (l) USDSGD

(m) USDBRL (n) USDCNY (o) USDINR (p) USDMXN

(q) USDPLN (r) USDRUB (s) USDTRY (t) USDZAR

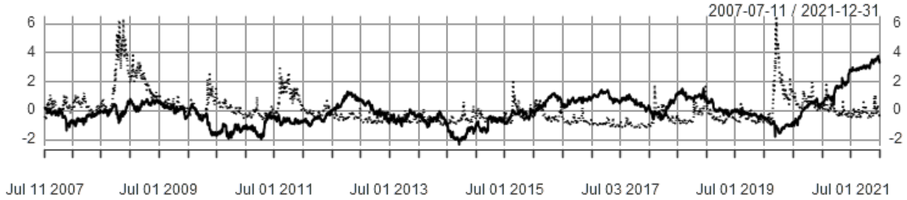
NOTES: The arrow in each panel shows the change in influence and dependence between the rolling samples ending on December 31, 2007, and December 31, 2021. The forecast horizon is 10 trading days and the window length is 250 trading days.

Figure 8: Change in Influence and Dependence between December 31, 2007 and December 31, 2021

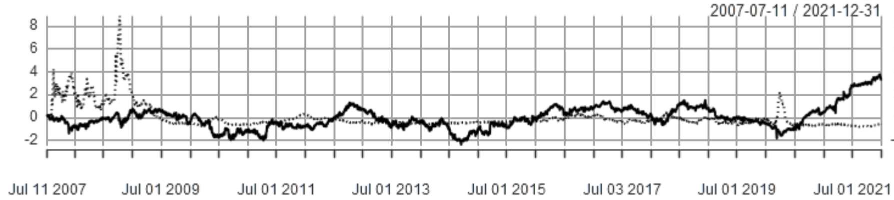


Notes: The top panel shows total portfolio flows into EMs (including both portfolio debt flows and portfolio equity flows), which are measured using the Institute for International Finance's monthly tracker. The unit of measurement is billions of US dollars. The net DM-to-EM spillover obtained using 250-day rolling samples and a 10-days-ahead forecast horizon is converted to monthly frequency using end-of-month values and is reported in the bottom panel. The unit of measurement is percent.

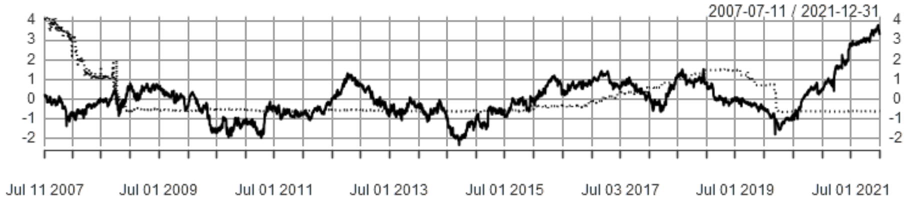
Figure 9: Total Portfolio Flows into EMs versus Net DM-to-EM Spillovers



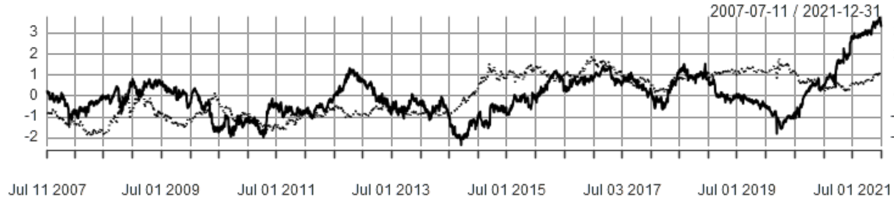
(a) Net DM-to-EM Spillover vs. the VIX



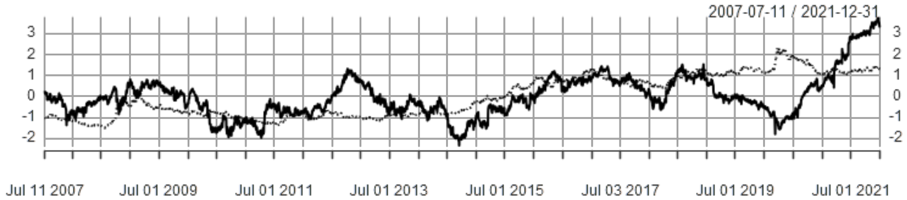
(b) Net DM-to-EM Spillover vs. the TED Spread



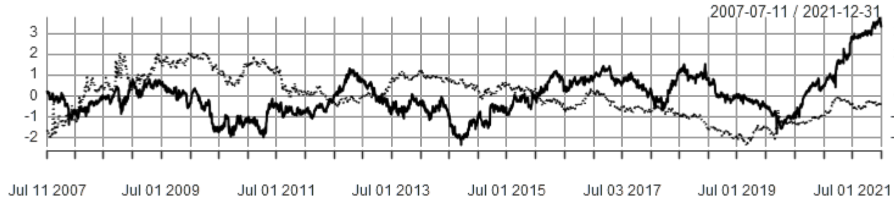
(c) Net DM-to-EM Spillover vs. the Effective Federal Funds Rate



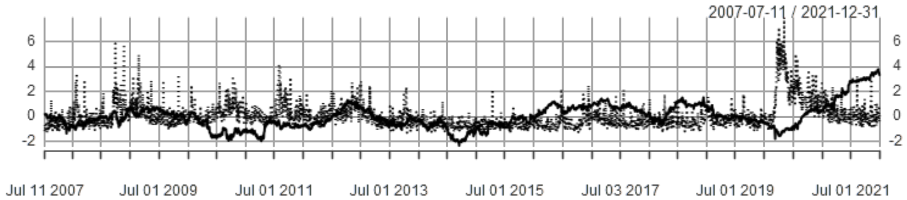
(d) Net DM-to-EM Spillover vs. the DXY Dollar Index



(e) Net DM-to-EM Spillover vs. the EM US Dollar Index

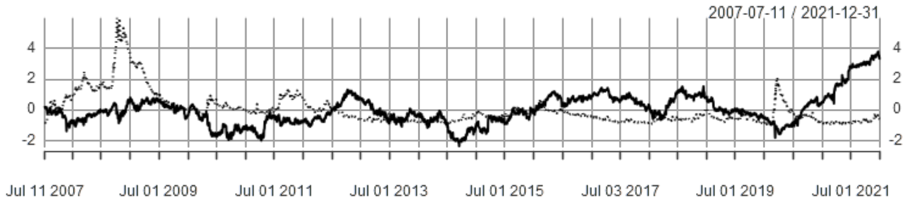


(f) Net DM-to-EM Spillover vs. the Slope of the US Yield Curve

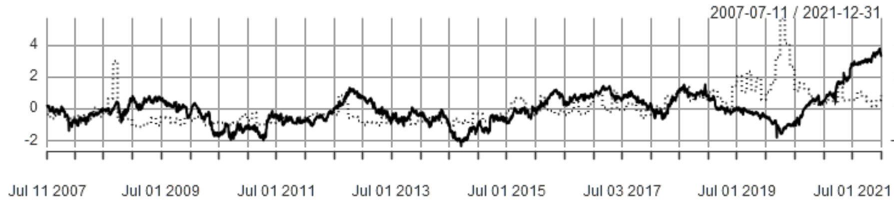


(g) Net DM-to-EM Spillover vs. Economic Policy Uncertainty

(h) Net DM-to-EM Spillover vs. the Gold Price



(i) Net DM-to-EM Spillover vs. Financial Stress

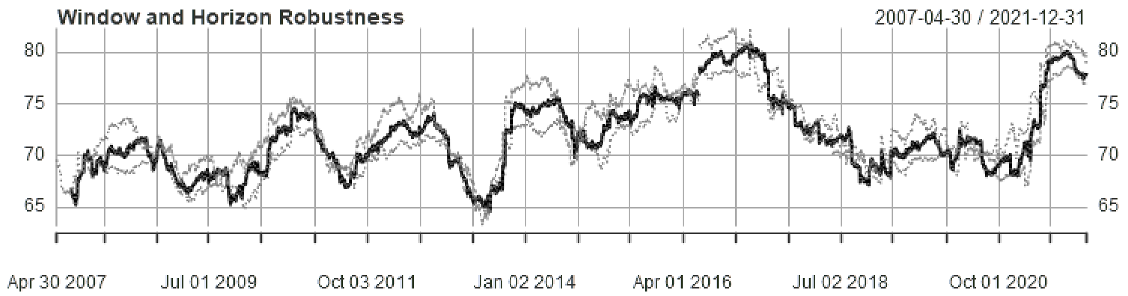


(j) Net DM-to-EM Spillover vs. US-China Tensions

Figure 10: Standardized Net DM-to-EM Spillover (solid lines) vs. Standardized Global Push Factors (dashed lines)

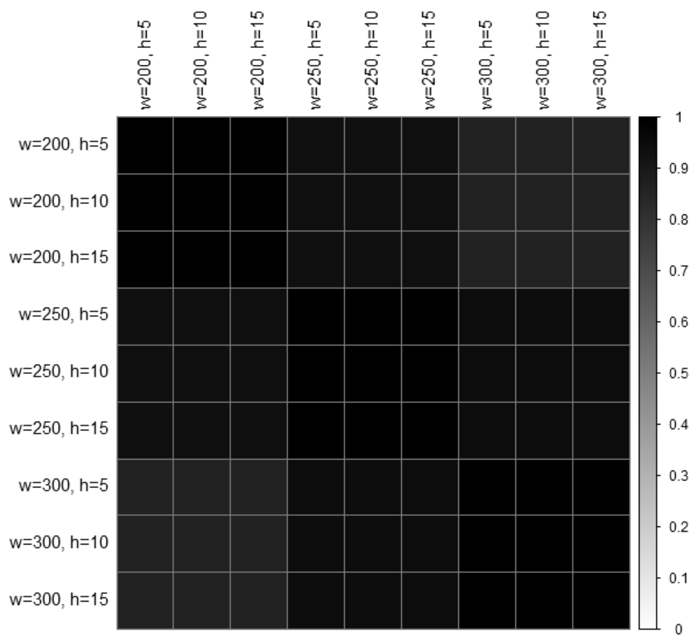
Appendix A: Robustness to Window and Horizon Selection

Figures A1 and A2 indicate that neither the choice of window length for the rolling sample analysis nor the choice of forecast horizon used to construct the GVD exerts a dominant influence on our results. Figure A1 shows that the disaggregate spillover indices obtained using all pairwise combinations of $w = \{200, 250, 300\}$ and $h = \{5, 10, 15\}$ trading days exhibit similar dynamics and share common peaks and troughs. To the naked eye, Figure A1 appears to show only three lines because, for a given window length, the choice of forecast horizon has a negligible effect on the spillover index, meaning that the three spillover indices for a given window length are almost indistinguishable from one-another. This is reflected in a clear block structure in Figure A2, as only changes in the window length result in any notable variation in pairwise correlation among the spillover indices. Nonetheless, all of the correlations reported in Figure A2 are strongly positive, with a median value of 0.942. Meanwhile, Tables A1 and A2 demonstrate the robustness of our auxiliary regression results to the use of alternative window lengths in the construction of the net DM-to-EM spillover.



NOTES: The figure plots the disaggregate spillover indices obtained using all pairwise combinations of $w = \{200, 250, 300\}$ and $h = \{5, 10, 15\}$ trading days. Results for our baseline setting with $w = 250$ and $h = 10$ trading days are shown in black, while results using the other combinations of parameters are shown in gray. The unit of measurement is percent.

Figure A1: Robustness to Variations in the Rolling Window and Forecast Horizon



NOTES: The figure shows the pairwise common sample correlation between the disaggregate spillover indices obtained using all pairwise combinations of $w = \{200, 250, 300\}$ and $h = \{5, 10, 15\}$ in the form of a heatmap.

Figure A2: Pairwise Common Sample Correlation among Spillover Indices obtained using Different Rolling Windows and Forecast Horizons

Table A1: Relations among the Net DM-to-EM Spillover and Global Push Factors, w=200

	Dependent variable: Net DM-to-EM Spillover											
Constant	−0.000	−0.000	−0.000	0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.170***	−0.171***
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.013)	(0.015)
VIX	−0.104***											−0.555***
	(0.012)											(0.028)
TED Spread		−0.082***										0.047
		(0.014)										(0.029)
Federal Funds Rate			−0.020									0.326***
			(0.013)									(0.041)
DXY Dollar Index				0.361***								−0.117***
				(0.014)								(0.043)
EM Dollar Index					0.472***							0.824***
					(0.018)							(0.050)
Slope of US YC						−0.240***						0.328***
						(0.013)						(0.039)
EPU Index							−0.043***					−0.167***
							(0.015)					(0.020)
Gold Price								0.229***				0.250***
								(0.018)				(0.033)
Financial Stress									−0.158***			0.551***
									(0.015)			(0.040)
US-China Tensions										0.232***		−0.269***
										(0.026)		(0.027)
COVID Indicator											1.294***	1.301***
											(0.071)	(0.086)
Adj. R-squared	0.011	0.006	0.000	0.130	0.223	0.057	0.002	0.052	0.025	0.054	0.191	0.421

NOTES: Heteroskedasticity and autocorrelation robust standard errors are reported in brackets beneath each parameter estimate. Statistical significance at the 10%, 5% and 1% significance level is denoted by *, ** and ***, respectively. All variables aside from the COVID indicator are standardized to maintain comparability with Figure 10 and to prevent scale differences from hampering comparisons across coefficients.

Table A2: Relations among the Net DM-to-EM Spillover and Global Push Factors, w=300

	Dependent variable: Net DM-to-EM Spillover											
Constant	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.121***	−0.068***
	(0.016)	(0.017)	(0.017)	(0.016)	(0.015)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)	(0.014)	(0.014)
VIX	−0.161***											−0.587***
	(0.012)											(0.032)
TED Spread		−0.069***										0.096***
		(0.012)										(0.029)
Federal Funds Rate			0.104***									0.230***
			(0.013)									(0.035)
DXY Dollar Index				0.351***								−0.443***
				(0.014)								(0.041)
EM Dollar Index					0.455***							1.311***
					(0.019)							(0.050)
Slope of US YC						−0.283***						0.302***
						(0.014)						(0.042)
EPU Index							−0.115***					−0.147***
							(0.015)					(0.020)
Gold Price								0.144***				0.241***
								(0.018)				(0.034)
Financial Stress									−0.183***			0.510***
									(0.014)			(0.042)
US-China Tensions										0.164***		−0.369***
										(0.025)		(0.027)
COVID Indicator											0.897***	0.500***
											(0.075)	(0.087)
Adj. R-squared	0.026	0.004	0.011	0.123	0.207	0.080	0.013	0.020	0.033	0.027	0.094	0.416

NOTES: Heteroskedasticity and autocorrelation robust standard errors are reported in brackets beneath each parameter estimate. Statistical significance at the 10%, 5% and 1% significance level is denoted by *, ** and ***, respectively. All variables aside from the COVID indicator are standardized to maintain comparability with Figure 10 and to prevent scale differences from hampering comparisons across coefficients.