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Portfolio Capital Flows and the US Dollar Exchange Rate: Viewed From the Lens of Time and Frequency Dynamics of Connectedness

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Abstract

Using high-frequency, proprietary data on daily net non-resident portfolio flows to emerging markets, our study finds in the time domain connectedness framework that, to varying degrees, there is less interconnectedness in non-resident debt and equity portfolio flows to our sample of emerging market (EM) economies during normal times. In contrast, during times of uncertainty and stress, the interconnectedness of portfolio flows intensifies. This indicates the notion of asymmetry in the spillovers of these portfolio flows during periods of stress relative to normal times. More importantly, over most of the sample period, we find that shocks in the broad EM US dollar exchange rate can have important effects on these interconnections where, based on estimates of the net directional spillover index, the broad EM US dollar exchange rate is a net transmitter of shocks to debt and equity portfolio flows of the EM economies. Using the more recent frequency domain approach to connectedness, we find that the broad EM US dollar exchange rate is a net transmitter of shocks to the EM economies' debt and equity flows with the impact of such shocks hitting portfolio capital flows within at least a week to 100 days. In addition to the importance of pre-emptive prudential policy levers, efforts toward better monitoring of risks can contribute to creditors and investors in EM economies becoming more resilient to global shocks, particularly, during times of US dollar appreciations when these portfolio flows tend to reverse.

Keywords: portfolio debt flows, portfolio equity flows, connectedness, directional spillover

JEL Classification Numbers: C58, F31, F41, G15

[*] *The views expressed herein are solely those of the authors and do not necessarily reflect the views of The SEACEN Centre and the SEACEN member central banks/monetary authorities.*

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1 Introduction

One of the notable findings in the large literature that developed to describe the striking behaviour of international capital flows during the period of the 1990s to the 2010s is that these flows are inherently pro-cyclical (Broner et al., 2013; Rey, 2013). In other words, these capital flows increase during times of expansions or risk-on behaviour among investors, and decrease during periods of uncertainty or risk-off behaviour. This pattern is particularly stronger for emerging market (henceforth EM) economies, for which the literature has coined the term “sudden stops” to refer to extreme situations of large collapses in these flows.[1] This in turn led to a corollary literature that attempted to uncover the drivers of these capital flows.[2] One important determinant identified by this literature is the role played by global factors in generating repeated episodes of booms and busts in capital flows. As earlier observed by Calvo et al. (1996), “global factors affecting foreign investment tend to have an important cyclical component, which has given rise to repeated booms and busts in capital inflows". Specifically, global or “push" factors such as global or advanced economy growth and external interest rates are found to be of most importance in generating such repeated episodes (Koepke, 2019; Mercado, 2020).

More recently, several studies have found that global factors such as the gyrations in the broad EM US dollar exchange rate are strongly associated with capital flows movements. For instance, Hofmann and Park (2020) argued that this broad US dollar exchange rate has characteristics of being a yardstick of global investor risk appetite. When investor risk appetite falls, investors and creditors cut back on their exposures from risky investments and borrowers which lead to US dollar appreciation, weakening of global economic activity and tightening of global financial conditions through capital flow reversals or reduced capital inflows. The converse result would occur if the appetite for risk by investors were to instead rise. Similar evidence is provided by Hofmann et al. (2017), Erik et al. (2020) and Avdjiev et al. (2019b).

A related mechanism works in what is dubbed the “risk-taking channel" of US dollar exchange

[1] The term is believed to have originated from a 1995 publication by Dornbusch and his co-authors (Dornbusch et al., 1995) where they quoted a banker's maxim - “it is not speed that kills, it is the sudden stop".

[2] For a comprehensive survey of this literature, refer to Koepke (2019) and Mercado (2020).

rate fluctuations by Bruno and Shin (2015a, 2015b).[3] According to this channel, in the presence of currency mismatch on the part of an EM corporate borrower (i.e., borrowed in dollars but hold domestic currency assets), an appreciation of the US dollar weakens the balance sheet of this EM corporate borrower whose liabilities rise relative to its assets. Its net worth and creditworthiness declines. From the perspective of the creditors, their capacity to extend additional credit declines because the likelihood of a loss happening due to an unexpected event, or, the tail risk in their overall credit portfolio increases (Hofmann & Park, 2020; Hofmann et al., 2017). The result is an overall decline in global dollar credit supply, dampening global economic activity and tightening global financial conditions, again through capital reversals or reduced capital inflows. If, instead, the US dollar depreciates, the same mechanism prevails, except that the relationships work in reverse in which case the balance sheet of borrowers strengthens allowing creditors to lend more, boosting economic activity in EM economies.[4] This risk-taking channel of US dollar exchange rate movements operates through the unique and pre-eminent role that the US dollar plays in international financial markets, for instance, in its use as the major currency in denominating debt contracts (Bruno & Shin, 2015b).[5]

The primary aim of our paper is to analyse the interconnections between net portfolio flows (debt and equity flows) to a select group of EM economies and the broad EM US dollar exchange rate. To do this, we use a high-frequency, proprietary data set on daily net non-resident portfolio flows to emerging markets for both debt and equity flows based on national sources for a number of EM economies compiled and regularly updated by the Institute of International Finance (IIF).[6] To our knowledge, our study is one of the first to provide empirical evidence on this interconnection

[3] The term risk-taking is adapted from an earlier study by Borio and Zhu (2012), who coined the term in the broader context of the transmission of monetary policy.

[4] This channel is often discussed alongside the so-called financial channel of exchange rate whereby the latter is believed to work in the opposite direction compared to the net exports channel. Under the net exports channel, a US dollar appreciation enhances economic activity in EM economies. In contrast, under the financial channel of the exchange rate, it operates through the liabilities side of the balance sheet of EM borrowers such that this time, a US dollar appreciation would depress economic activity through a weakened balance sheet of EM borrowers (Avdjiev et al., 2019a). Kearns and Patel (2016) provide empirical evidence that the financial channel partly offsets the trade channel for EM economies, but the effect is weaker for advanced economies.

[5] As emphasised by Maggiori et al. (2019), this pre-eminent role of the US dollar carries important benefits for the US economy in the form of lower costs of borrowing than it otherwise would, as shown by Gourinchas and Rey (2007); Maggiori et al. (2020).

[6] Koepke and Paetzold (2020) provide a useful overview of the capital flows data compiled by the IIF and its differences with another high frequency portfolio flows data set such as the Emerging Portfolio Fund Research (EPFR).

by leveraging on this high-frequency portfolio flows data compiled by the IIF.[7]

In conducting the empirical analysis, our approach is to first construct separate measures of daily net non-resident portfolio flows interdependence (connectedness) for debt and equity flows based on the vector autoregression framework of Diebold and Yilmaz (2009, 2012, 2014) (henceforth DY). From these quantitative measures of interdependence, we examine notably, how the interconnections of these flows evolve over time for a select group of EM economies, particularly, during calm and turbulent times. Also following the standard framework proposed by DY, our next approach is to construct quantitative estimates of the directional spillover, the calculations of which come directly from our measures of connectedness. These spillover measures allow, for instance, the assessment of how shocks in the broad EM US dollar exchange rate affect the interconnections in daily net non-resident portfolio flows over time.

It must be noted at this point, however, that the framework developed by DY focuses only on the time domain. Recently, Baruník and Křehlík (2018) (henceforth BK), extended this time domain framework of DY to the frequency domain. The advantage of working also with the frequency domain is that it enables us to determine whether shocks to a particular variable gets transmitted to the other variables in the short-term (i.e., high frequency) or long-term (i.e., low frequency). In this paper, besides employing the framework developed by DY, we also follow the approach of BK. This allows us to determine whether shocks to the broad EM US dollar exchange rate gets transmitted to the EM economies' net non-resident portfolio debt and equity flows in the short-term or long-term.

The main reason that interconnections may vary across frequencies is the heterogeneity of numerous market participants (investor base) that interact within international and domestic financial markets (He et al., 2019). Specifically, these agents operate at different time horizons which are represented by the frequencies that, for instance, range from a matter of minutes to several quarters because these agents have different objectives, preferences, risk tolerance and institutional constraints. Thus, shocks can transmit through markets that produce heterogeneous frequency responses. Examples of agents with short investment horizons are those of traders, hedge funds and

[7] Another is the study by Karagedikli and Rummel (2022).

money market funds that are more concerned with the short-run performance of their investments, whereas, agents like large institutional investors (e.g., pension funds, big insurance companies and sovereign wealth funds) care more about the long-run performance of the markets (Ferrer et al., 2018).

The approaches of DY and BK have been employed together in a few previous studies to analyse such issues as the following: the spillover between returns and volume in the cryptocurrency markets (Fousekis & Tzaferi, 2021), the extent of connectedness across cryptocurrencies (Aslanidis et al., 2021), the spillovers between cryptocurrencies and other financial assets (Corbet et al., 2018), the spillovers among major cryptocurrencies in normal times and during the COVID-19 outbreak (Kumar et al., 2022), the spillovers between EU carbon prices, major commodity prices, US S&P 500 stock and the US dollar (Adekoya et al., 2021), the spillovers between renewable energy stocks and crude oil prices (Ferrer et al., 2018), the spillovers between major precious metals and major currency markets (Mensi et al., 2021), and the spillover across Asia-Pacific currencies (Anwer et al., 2022). In spite of the diversity of topics to which both approaches have been employed, our study is the first, to our knowledge, to employ the approaches of DY and BK (i.e., in a time and frequency domain setting) to analyse the issue of the interconnection between daily net portfolio flows and the broad EM US dollar exchange rate for a sample of EM economies.

Using the time domain approach of DY, our results show that, to varying extent, there is a less interconnected system of net non-resident portfolio flows in our sample of EM economies during calmer or normal times. In contrast, during turbulent times, the interconnections of these portfolio flows to EM economies are higher. We also observe, based on visual inspection that during times when there are greater interconnections in net non-resident portfolio flows, the US dollar tends to appreciate, in general, against a basket of EM currencies. More importantly, we find that shocks in the broad EM US dollar exchange rate can have important effects on these interconnections where, based on estimates of the net directional spillover index, the broad EM US dollar exchange rate is a net transmitter of shocks to the EM economies' debt and equity flows over most of the sample period. We also find that, in general, during episodes that the broad EM US dollar exchange rate is a net transmitter of shocks, the US dollar tends to appreciate against the basket of EM currencies. Using the frequency domain approach of BK, our results show that, over most of the sample period, the broad EM US dollar exchange rate is a net transmitter of shocks to the EM economies' debt and equity flows more at the medium-term (from 5 to 20 days) and long-term frequencies (from 20 days to 100 days) rather than at the short-term frequency (up to 5 days). This suggests that shocks to the EM US dollar exchange rate gets transmitted to the EM economies' portfolio flows basically within at least a week to 100 days.

Our work is related to the voluminous literature on global spillovers. One strand of this literature to which our paper is connected is on the supposed existence of a global financial cycle in capital flows and asset prices (Miranda-Agrippino & Rey, 2020a; Rey, 2016) and the effect of US monetary policy on this global financial cycle (Miranda-Agrippino & Rey, 2020b). Our paper is also related to another strand of this literature on global spillovers that deals with the international spillovers of US monetary policy shocks (Banerjee et al., 2016; Dedola et al., 2017; Georgiadis, 2016; Iacoviello & Navarro, 2019; Lodge & Manu, 2022).

This paper is organised as follows. The next section presents the approaches of DY and BK that we employ to achieve the objectives of the study. Section 3 discusses the data and presents some descriptive statistics. Section 4 presents the main empirical results of our study. Section 5 discusses the tests we conduct to check the sensitivity of our results. Concluding remarks are offered in Section 6.

2 Method

DY put forward a connectedness measure in the time-domain that relies on the forecast error variance decomposition (FEVD). Specifically, the generalised identification framework proposed by Koop et al. (1996) and Pesaran and Shin (1998) that is invariant to the ordering in a vector autoregression (VAR) of N endogenous variables is used. This generalised forecast error variance decomposition (GFEVD) of a variable into components attributable to shocks to the individual N variables in the VAR for a forecast horizon H can be calculated as:

$$(\theta_H)_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H} \left(\left(\Psi_h \sum \right)_{ij} \right)^2}{\sum_{h=0}^{H} \left(\Psi_h \sum \Psi_h' \right)} \tag{1}$$

where Ψ_h is a $n \times n$ matrix of moving average coefficients at lag h above. σ_{jj} is the jth diagonal element of the $\sum$ matrix. The $(\theta_H)_{i,j}$ refers to the contribution of the jth variable to the variance of forecast error of the ith variable at horizon h.

Because the rows of the variance decomposition matrix θ_H do not necessarily equal to one, each entry in the matrix is normalised by the row sum as:

$$(\tilde{\theta}_H)_{i,j} = \frac{(\theta_H)_{ij}}{\sum_{j=1}^{n} (\theta_H)_{ij}} \tag{2}$$

$(\tilde{\theta}_H)_{i,j}$ provides a measure of pairwise connectedness from i to j at horizon h. This information can be aggregated to estimate the overall connectedness of the system. Furthermore, we can also estimate the directional spillovers transmitted by a particular variable i to the remaining variables, j and by the j variable from all the other i variables. The net spillovers would be the difference between the directional spillovers to and from these variables with positive values suggesting that a particular variable i is a net transmitter of shocks, while negative values suggest that it is a net receiver of shocks.[8]

BK extended DY's connectedness measure to the frequency domain. They use a frequency response function which is obtained from the Fourier transform of the moving average coefficients $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h} \Psi_h$, where ω denotes the frequency and i is an imaginary constant. Specifically, the generalised forecast error variance decompostion at a particular frequency can be computed as:

$$(\theta_\omega)_{i,j} = \frac{\sigma_{jj}^{-1} \left| \left(\Psi(e^{-i\omega}) \sum \right)_{ij} \right|^2}{\left(\Psi(e^{-i\omega}) \sum \Psi'(e^{+i\omega}) \right)_{ii}} \tag{3}$$

where $(\theta_\omega)_{i,j}$ is the portion of the spectrum ith variable at a given frequency ω due to shocks in the jth variable. Notice that the forecast horizon H does not play a role in this regard.

Similar to the case of the time domain connectedness analysis of DY, (3) can be normalised as:

$$(\tilde{\theta}_\omega)_{i,j} = \frac{(\theta_\omega)_{ij}}{\sum_{h=1}^{n} (\theta_\omega)_{ij}} \tag{4}$$

[8] We refer to DY for all the equations required to obtain these various measures. We do not repeat them here.

In applications relevant to economics and finance, working with frequency bands, $d=(a,b)$ can be more interesting in terms of examining short-, medium- or long-term connectedness rather than connectedness at a particular frequency. For an arbitrary frequency band, this can be calculated as:

$$(\tilde{\theta}_d)_{i,j} = \int_a^b (\tilde{\theta}_\omega)_{ij} d\omega \tag{5}$$

At this point, BK provided a variety of measures which are inspired by the total connectedness and directional spillovers introduced by DY. For example, within a certain frequency band d, the overall connectedness and net pairwise connectedness between two variables i and j can each be calculated.[9] The calculations of these measures both at the time and frequency domains are carried out in a dynamic setting. In particular, a rolling window of 100 days with a moving window step of one day is set up. In each step, the VAR is estimated with two lags. The generalised forecast error variance decomposition is based on a forecast horizon H of 100 days.[10]

3 Data

The data for this study consist of the daily net non-resident portfolio flows (in million USD) to a select group of EM economies both for debt and equity flows, and the daily broad EM US dollar exchange rate. For net non-resident debt flows, the data consists of the flows to seven EM economies, namely, India, Indonesia, Hungary, Mexico, Poland, South Africa and Thailand, while for net non-resident equity flows, these are the flows to the EM economies of Brazil, India, Indonesia, Korea[11], Philippines, South Africa and Thailand. All these data on net non-resident debt and equity flows are obtained from the data set compiled and regularly updated by the Institute for International Finance (IIF). We note that our select group of EM economies are by no means exclusive, for the IIF also compiles data on net non-resident portfolio flows of other EM economies. Our choice of which country to include in our analysis is dictated by the availability of complete daily data on these flows over our period of examination. The data on daily broad EM US dollar exchange rate is obtained from FRED and can be accessed at this specific site: `https://fred.stlouisfed.org/`

[9] We refer to BK for all the equations required to obtain these various measures. We also do not repeat them here.
[10] In carrying out the techniques of DY and BK, we use the frequencyConnectedness package in R which was developed by Tomas Křehlík.
[11] In this study, Korea refers to the Republic of Korea.

series/DTWEXEMEGS. We use the logarithmic first differences (multiplied by 100) of this daily broad EM US dollar exchange rate in our analysis. The sample period is from January 2, 2015 to April 29, 2022, which gives us a total of 1824 daily observations.

Columns (1) to (7) of Table 1 provides the results of the unit root test and summary statistics of our data on net non-resident debt flows to the seven pertinent EM economies. Over our sample period, the average net non-resident portfolio debt flows to India Indonesia, Hungary and Thailand is positive, which means that these countries experienced, on average, an increase in non-resident debt inflows. In contrast, during the same sample period, the average net non-resident debt flows to Mexico and South Africa is negative which suggests that these two countries underwent, on average, a decrease or reversal in non-resident debt inflows. The net non-resident debt flows to Mexico is the most volatile followed by Poland. There is no clear pattern of skewness in the underlying distribution of the data. The skewness measure is negative for Mexico, Poland and South Africa, while it is positive for the rest of the economies' net non-resident debt flows. The kurtosis coefficient is always greater than 3, indicating that all the data on net non-resident debt flows to our pertinent EM economies have fat tails and more peakedness compared to the Gaussian distribution. This departure from a normal distribution is supported by the Jarque-Bera test statistics, which rejects the null hypothesis of a normal distribution for all our data on net non-resident debt flows at the 1% level. The results of the ADF unit root tests reveal that these same data series are all stationary at the 1% level. The last column of Table 1 reports the unit root test and summary statistics on our broad EM US dollar exchange rate (in log differences). It shows that, on average, the US dollar appreciated against a broad basket of EM currencies during the sample period. Its measure of skewness is positive and the kurtosis coefficient is greater than 3 which suggest heavy tails and more peakedness relative to the Gaussian distribution. The Jarque-Bera test statistics is significant at the 1% level, indicating evidence of departure from normality. Lastly, this series is stationary according to the ADF test at the 1% level.

The first seven columns of Table 2 provide the results of the unit root test and summary statistics of our data on net non-resident equity flows to the relevant EM economies. During the same sample period, five (i.e., Brazil, Korea, Philippines, South Africa and Thailand) out of the seven EM economies experienced, on average, a decrease or reversal in non-resident inflows, while the rest underwent an increase in non-resident inflows. The net non-resident equity flows to Korea is the most volatile followed by India. Similar to Table 1, there is no clear pattern of skewness in the underlying distribution of the data with the measure being negative for Brazil, Korea and South Africa, whereas it is positive for India, Indonesia, Philippines and Thailand. Likewise, the kurtosis coefficient is always greater than 3, indicating that all the data on net non-resident equity flows to our EM economies have heavy tails and more peakedness relative to the Gaussian distribution. This departure from normality is also confirmed by the Jarque-Bera test statistics. The results of the ADF unit root test further reveal that all our data series on net non-resident equity flows are stationary at the 1% level. Finally, for ease of reference, the last column of Table 2 repeats the reported unit root test and summary statistics on our broad EM US dollar exchange rate, which was previously discussed above.

4 Main empirical results

Let us first analyse the dynamic estimates of the total connectedness computed based on the DY framework. The moving window estimates are illustrated in Figure 1 for net non-resident debt flows, while Figure 2 illustrates our estimates for net non-resident equity flows. In each figure, there are two dynamic estimates of total connectedness. The red coloured lines in both figures are the connectedness measures calculated from our original generalised forecast error variance decomposition where the endogenous variables in the system are the net non-resident portfolio debt and equity flows of the individual EM economies in figures 1 and 2, respectively. On the other hand, the blue coloured lines in both figures represent the connectedness measures calculated from a generalised forecast error variance decomposition that not only includes our respective original set of endogenous variables, but also the broad EM US dollar exchange rate (in log differences), as one of the endogenous variables. These red and blue coloured lines clearly exhibit similar patterns, and all show substantial variation over the course of the sample period.

To varying degrees, total connectedness appears to be related to various major economic and financial events, in that it tends to fall or bottom out during calmer times, suggesting that less economic and financial uncertainty brings about a less interconnected system of net non-resident portfolio flows to EM economies. In contrast, connectedness tends to rise or peak during turbulent times where the high uncertainty leads to a more interconnected system or spillovers. Such is the case during the 2015 plunge in oil prices, the 2016 Brexit referendum, the 2017 US Federal Reserve increase in interest rates, the 2018 US and China trade tensions, the 2019 Chinese yuan depreciation, the 2020 COVID-19 pandemic, and the February 2022 Russian invasion of Ukraine. These results support the notion of asymmetry in the interconnections or spillovers of these portfolio flows during periods of stress compared to normal times. In addition, these results are in line with those found in the financial and energy markets where interconnections tend to increase during times of heightened uncertainty (Baruník & Křehlík, 2018; Ferrer et al., 2018; Mensi et al., 2021). As observed by Ferrer et al. (2018), "when uncertainty reigns, any positive or negative information is reviewed and processed more thoroughly, thus generating increased interconnectedness".

Two further important findings can be distilled from figures 1 and 2. First, it appears that during episodes where we observe greater interconnections in net non-resident portfolio flows to our sample of EM economies, the broad EM US dollar exchange rate (green coloured line) tends to rise (i.e., the US dollar appreciates against the basket of EM currencies). Second, shocks in the broad EM US dollar exchange rate can have important effects on these interconnections in net non-resident portfolio debt and equity flows over time. Specifically, beyond exhibiting similar patterns, the magnitude of the connectedness calculated from a generalised forecast error variance decomposition that includes the broad EM US dollar exchange rate as one of the endogenous variables (again, the blue coloured lines in both figures), tends to be relatively larger than the connectedness measure that excludes this same variable in the generalised forecast error variance decomposition (again, the red coloured lines in both figures), during the entire sample period. For instance, in figure 1, the minimum and maximum values are 12% and 43%, respectively, for the blue coloured line, while these are at 9% and 31%, respectively, for the red coloured line. In figure 2, the minimum and maximum values are 13% and 89%, respectively, for the blue coloured line, whereas these are at 9% and 86%, respectively, for the red coloured line.

From our calculated connectedness measures, we in turn delve deeper in our analysis by obtaining the net directional spillover information of the broad EM US dollar exchange rate over time. The calculation of these net directional spillover indices is done using the time domain approach of DY, and are plotted in figures 3 and 4 for net non-resident debt flows and net non-resident equity flows, respectively. Recall that a positive value of the net directional spillover index of the broad EM US dollar exchange rate means that this variable is a net transmitter of shocks to the EM economies' net non-resident portfolio flows, while a negative value indicates that this same variable is a net receiver of shocks coming from the EM economies' net non-resident portfolio flows. Just as the previous connectedness measures, the net directional spillovers exhibit substantial time variation with peaks generally reached during turbulent and highly uncertain times attributed to major global events that were enumerated above. In both figures, the highest net directional spillovers were reached during the COVID-19 pandemic. More importantly, we can observe from both figures that over most of the sample period, the broad EM US dollar exchange rate is a net transmitter of shocks to the debt flows (figure 3) and equity flows (figure 4) of the EM economies. In figure 3, for instance, as a proportion of the total number of observations, 68% of the calculated net directional spillover of the broad EM US dollar exchange rate take on positive values, while in figure 4, the proportion of positive values stand at 76%. Furthermore, we can also observe in both figures that, in general, during episodes that the broad EM US dollar exchange rate is a net transmitter of shocks, the US dollar tends to appreciate against the basket of EM currencies (green coloured line).

Figures 5 and 6 plot the dynamics in the frequency domain of the net directional spillover of the broad EM US dollar exchange rate by decomposing these dynamics into higher (up to 5 days), intermediate (from 5 to 20 days) and lower (from 20 days to 100 days) frequency bands based on the frequency domain approach to connectedness by BK. It must be noted at this point that these two figures break down the net directional spillover indices illustrated in figures 3 and 4, into highest (blue coloured line), intermediate (red colored line) and lowest (green colored line) frequencies.[12] As earlier discussed, the benefit of working with the frequency dynamics of the net directional spillover indices is that one can ascertain whether shocks in the broad EM US dollar exchange rate impact the system in the short-term (highest frequency), medium-term (intermediate frequency) or long-term (lowest frequency). As can be seen from figures 5 and 6, the broad EM US dollar exchange rate is a net transmitter of shocks to the EM economies' debt (figure 5) and equity (figure 6) flows more at the medium-term and long-term frequencies over most of the sample period. The basis for this finding is that as a proportion of the total number of observations in each frequency

[12] The sum of these three frequencies at each period is equal to the net directional spillover indices at the time domain.

bands, in figure 5, for example, 75% and 78% of the total observations in the medium-term and long-term frequencies, take on positive values, respectively, while for the short-term frequency this is at 58%. In figure 6, the percentage of positive values are at 87% and 86% for the medium-term and long-term frequencies, respectively, whereas this is at 64% for the short-term frequency. This suggests that shocks to the EM US dollar exchange rate gets transmitted to the EM economies' portfolio flows basically within at least a week to 100 days. Also in both figures, the largest net directional spillovers that were reached during the COVID-19 pandemic occurred at these same two frequencies.[13]

5 Robustness tests

In this section, to examine the sensitivity of our main empirical results, we present our robustness tests along two dimensions, namely (1) we estimate the VAR with 6 lags rather than at 2 lags; and (2) the generalised forecast error variance decomposition is based on a forecast horizon H equal to 200 days instead of what was set in the main results of 100 days. With regard to our first robustness test, using the time domain approach of DY, our finding that, to varying extent, there is a more interconnected system of net non-resident portfolio flows to our sample of EM economies during times of turmoil and vice-versa still holds. This is the case both for portfolio debt flows A1 and portfolio equity flows A2. Furthermore, our visual observation of US dollar appreciations against a basket of EM currencies during times when there are greater interconnections in net non-resident portfolio flows still holds for most periods. More importantly, the finding that shocks in the broad EM US dollar exchange rate have important effects on these interconnections in net non-resident portfolio debt and equity flows over time is validated. For instance, just as in the main results, the magnitude of the connectedness calculated from a generalised forecast error variance decomposition that includes the broad EM US dollar exchange rate as one of the endogenous variables (the blue colored lines in figures A1 and A2) tends to be relatively larger than the connectedness measure that excludes this same variable in the generalised forecast error variance decomposition (the red colored lines in both figures), during the entire sample period. The other important justification

[13] In figure 5, the highest frequency band registered its largest net directional spillover also during this period. However, this was not evident in figure 6.

comes from our calculated net directional spillover index of the broad EM US dollar exchange rate for which we discuss next.

Just as in the main results, as depicted by figures A3 and A4, the broad EM US dollar exchange rate is a net transmitter of shocks to the EM economies' debt flows (figure A3) and equity flows (A4), over most of the sample period. In the former, as a proportion of the total number of observations, 67% of the calculated net directional spillover of the broad EM US dollar exchange rate takes on positive values, while in the latter, the proportion of positive values is at 54%. Also, in both figures, the highest net directional spillovers were reached during the COVID-19 pandemic, while in general, during episodes that the broad EM US dollar exchange rate is a net transmitter of shocks, the US dollar tends to appreciate against the basket of EM currencies (green coloured line), particularly, in the case of debt flows. Finally, using the frequency domain approach of BK, the finding that the broad EM US dollar exchange rate is a net transmitter of shocks to the EM economies' debt and equity flows, more at the medium-term and long-term frequencies over most of the sample period, remains (i.e., shocks to the EM US dollar exchange rate still gets transmitted to the EM economies' portfolio flows within 5 to 100 days). These are presented in figures A5 and A6 where as a proportion of the total number of observations in each frequency bands, 77% and 78% of the total observations in the medium- and long-term frequencies, respectively, take on positive values in figure A5, while it is only at 51% for the short-term frequency. In figure A6, the percentage of positive values are at 67% and 77% for the medium- and long-term frequencies, respectively, whereas, it is much lower for the short-term frequency at 35%.

With regard to the second robustness test, the pertinent results using the approach of DY are presented in figures A7 to A10, while the results employing the approach of BK are shown in figures A11 to A12. We can see from these figures that there is very little difference compared to our main results. Thus, our main results discussed in the previous section is also robust to this sensitivity check we have undertaken in this part of our study.

6 Conclusion

A new frontier of literature is evolving that attempts to understand the effects and policy implications of EM capital flow dynamics, notably portfolio flows, from movements of the US dollar exchange rate vis-à-vis EM currencies. Indeed, the broad US dollar exchange rate serves as a barometer of global investor risk appetite. When investor risk appetite falls, the decision by investors to reduce their exposures lead to capital flow reversals or reduced capital inflows in EMs. On the other hand, if the risk appetite was to rise instead, there tends to be an increase in cross-border capital flows. Using high-frequency data on daily net non-resident portfolio flows to emerging markets for both debt and equity flows, this paper contributes to this growing literature by examining this supposed nexus between net portfolio flows to a select group of EM economies and the broad US dollar exchange rate. In this study, we take a different tack by analysing this nexus from the perspective of interconnectedness and spillovers over the period January 2, 2015 to April 29, 2022. To do this, we employ the connectedness framework proposed by DY in the time domain and the recent extension of this framework to the frequency domain by BK.

Using the time domain approach of DY, we find that, to varying extent, there is less interconnectedness across non-resident debt and equity portfolio flows in EMs during calmer or normal times. However, the interconnectedness of portfolio flows intensifies during turbulent times. These results provide support to the existence of asymmetry in portfolio capital flows during stressful times relative to calmer periods. Furthermore, upon visual inspection, we observe that during times when there are greater interconnections in net non-resident portfolio flows, the US dollar tends to appreciate in general against a basket of EM currencies. More importantly, we find that shocks in the broad EM US dollar exchange rate can have important effects on these interconnections in net non-resident portfolio debt and equity flows over time. Specifically, over most of the sample period, based on quantitative estimates of the net directional spillover index, the broad EM US dollar exchange rate is a net transmitter of shocks to the EM economies' debt and equity flows, for which the highest net directional spillovers were reached during the COVID-19 pandemic. In addition, we also find that, in general, during episodes that the broad EM US dollar exchange rate is a net transmitter of shocks, the US dollar tends to appreciate against the basket of EM currencies. Using the frequency domain approach of BK, we find that the broad EM US dollar exchange rate is a net transmitter of shocks to the debt and equity flows of EM economies, more at the medium-term and long-term frequencies over most of the sample period, that is, shocks to the EM US dollar exchange rate gets transmitted to the EM economies' portfolio flows within 5 to 100 days.

Studies have shown that more interconnected networks are more prone to systemic instability under large negative financial shocks, especially when these shocks are combined with short-term funding, imperfect information, and other financial frictions. For instance, Caballero and Simsek (2013) argue that the complexity of interconnected networks is a dormant factor in normal times; however, when adverse shocks hit, the complexity of these interconnections in conjunction with uncertainty can become a source of instability. Our study shows that a global factor such as the movements of the US dollar vis-'a-vis EM currencies make these interconnections across EM portfolio capital flows particularly acute during times of uncertainty and stress. Such spillover dynamics coming from the US dollar exchange rate to EM portfolio capital flows are likely amplified by contributing factors such as short-term funding, liquidity mismatches and leverage, especially given that intermediation of EM portfolio capital flows markedly shifted to the non-bank financial sector since the aftermath of the GFC. This latter phenomenon works toward making these non-financial firms deeply embedded into the domestic financial sector of EMs with potential systemic implications for the rest of the economy. Under these circumstances, there is no room for complacency on the part of authorities in EMs. It is in their best interest that, in addition to having sufficient buffers and pre-emptive prudential policy levers, they strengthen and enforce disclosure requirements on these non-bank financial institutions with respect to their exposures, including the amount of funding these firms obtain in the US dollar market. This can contribute towards better monitoring of risks, and making these entities more resilient to global shocks, particularly, during times of US dollar appreciations when these portfolio capital flows tend to reverse.

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Table 1: Descriptive statistics and unit root test of the daily net non-resident portfolio debt flows (in million USD) of the eight selected EM economies and the broad EM USD exchange rate

	India (1)	Indonesia (2)	Hungary (3)	Mexico (4)	Poland (5)	South Africa (6)	Thailand (7)	EM USD exchange rate (8)
Mean	3.1598	16.9355	0.9793	-14.1777	-9.3100	-11.1404	19.4411	0.0104
Maximum	1464.190	1500.00	860.4106	6522.905	1437.234	467.161	913.980	2.157
Minimum	-1542.250	-1083.680	-705.271	-4229.099	-1914.273	-775.629	-528.670	-1.875
Std. Dev.	175.8705	168.7022	130.1144	520.8560	254.9155	120.9398	136.4740	0.3412
Skewness	0.0412	0.340	0.2998	-0.5895	-0.1055	-0.8715	1.4219	0.5281
Kurtosis	19.4405	9.8633	8.0183	26.5151	7.0958	7.6689	9.3605	6.3637
JB	20542.65***	3615.085***	1941.248***	42130.52***	1278.345***	1887.608***	3689.338***	944.6746***
ADF	-14.01***	-18.02***	-46.80***	-44.19***	-45.87***	-12.77***	-27.92***	-41.41***

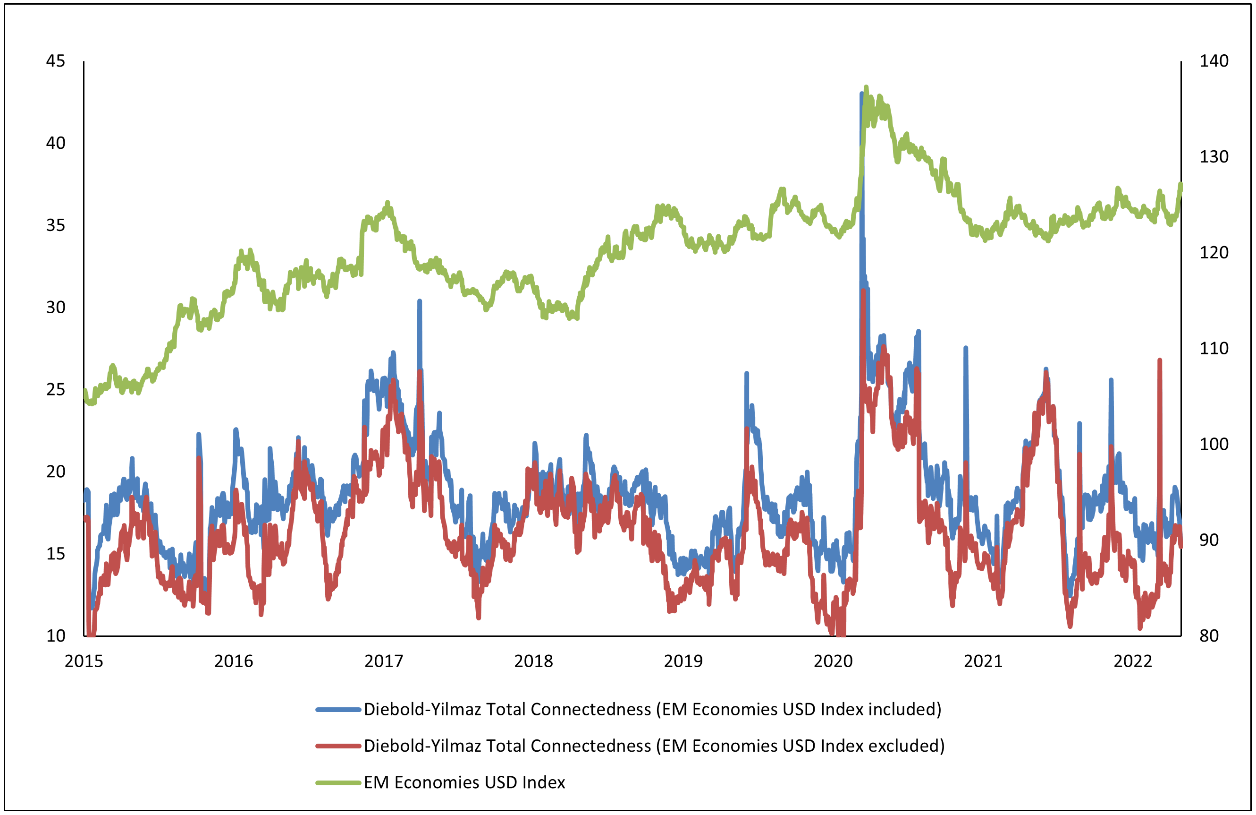
*Note: This table presents some summary statistics and unit root test for the daily series over the period from January 2, 2015 to April 29, 2022. The names of the EM countries denote their respective daily series on net portfolio debt flows (in million USD). The broad EM USD exchange rate series is in logarithmic first differences (multiplied by 100). JB refers to the Jarqe-Bera test statistics for normality. ADF is the Augmented Dickey- Fuller unit root test. *** indicates statistical significance at the 1% level.*

Table 2: Descriptive statistics and unit root test of the daily net non-resident portfolio equity flows (in million USD) of the eight selected EM economies and the broad EM USD exchange rate

	Brazil (1)	India (2)	Indonesia (3)	Korea (4)	Philippines (5)	South Africa (6)	Thailand (7)	EM USD exchange rate (8)
Mean	-0.58672	14.7734	0.2733	-24.140	-2.0487	-19.5610	-10.5050	0.0104
Maximum	1022.607	2599.770	3666.990	1695.520	1589.890	435.8810	625.5200	2.157
Minimum	-1224.867	-1118.760	-828.7110	-2688.680	-523.4320	-980.6020	-387.530	-1.875
Std. Dev.	162.5706	264.3120	117.4282	310.1011	51.0115	102.2077	68.5023	0.3412
Skewness	-0.1283	1.8713	17.9936	-1.6196	18.9689	-1.4201	0.7151	0.5281
Kurtosis	9.9878	18.0623	544.2423	15.4875	564.3048	16.5870	11.7247	6.3637
JB	3716.072***	18306.92***	22362111***	12648.67***	24054177***	14643.18***	5940.664***	944.6746***
ADF	-11.49***	-14.05***	-40.33***	-22.88***	-41.03***	-24.44***	-13.47***	-41.41***

*Note: This table presents some summary statistics and unit root test for the daily series over the period from January 2, 2015 to April 29, 2022. The names of the EM countries denote their respective daily series on net portfolio equity flows (in million USD). The broad EM USD exchange rate series is in logarithmic first differences (multiplied by 100). JB refers to the Jarqe-Bera test statistics for normality. ADF is the Augmented Dickey- Fuller unit root test. *** indicates statistical significance at the 1% level.*

Figure 1: Diebold-Yilmaz total connectedness index (daily net non-resident portfolio debt flows) and broad EM USD index: Main empirical results



Notes: This figure displays the time-varying/dynamic estimates of connectedness based on the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM US dollar exchange rate. The red coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition where the endogenous variables are the individual EM economies' net non-resident portfolio debt flows (left axis). The blue coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition that includes the individual EM economies' net non-resident portfolio debt flows plus the broad EM US dollar exchange rate (in log differences) (left-axis). Both time-varying/dynamic estimates of connectedness are calculated from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with two lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure 2: Diebold-Yilmaz total connectedness index (daily net non-resident portfolio equity flows) and broad EM USD index: Main empirical results

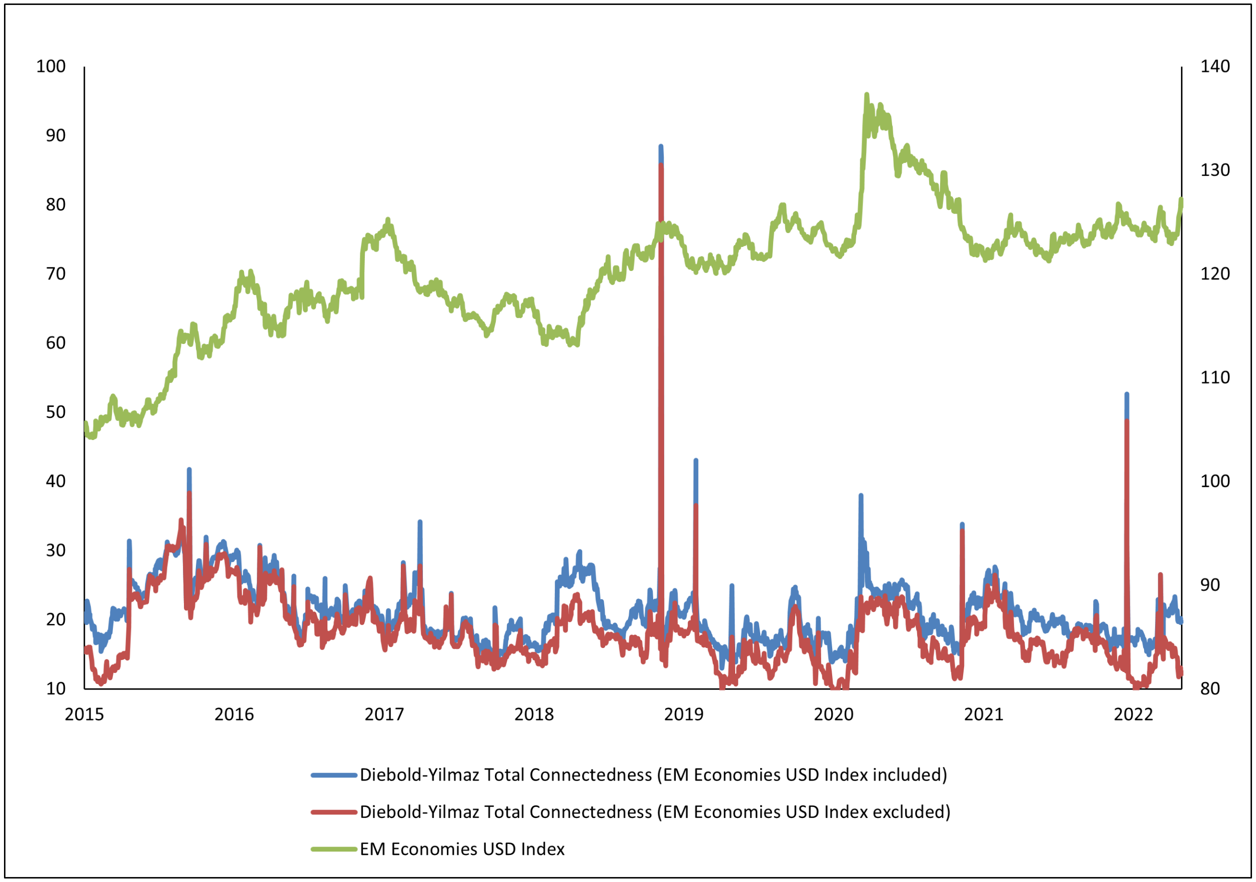


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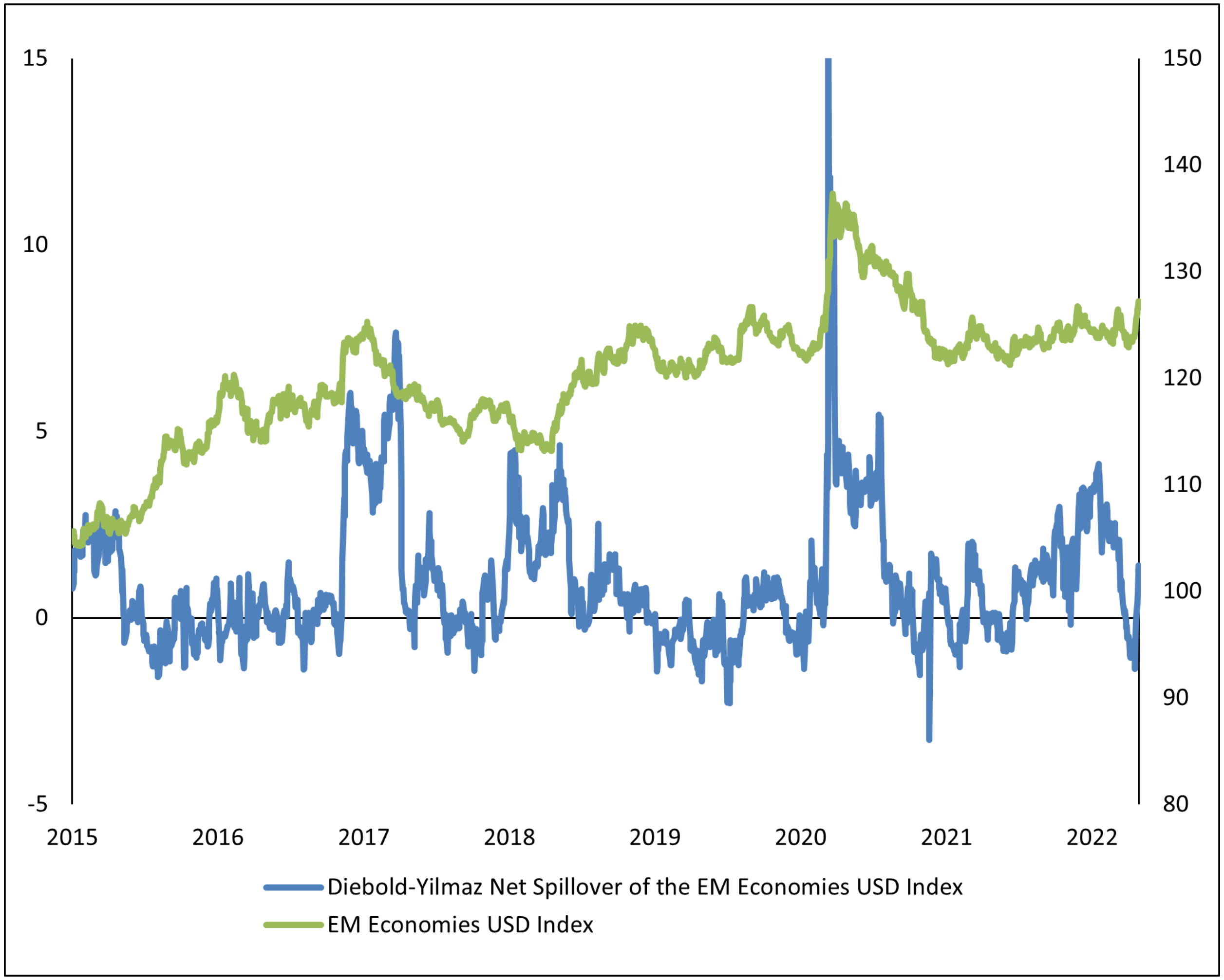
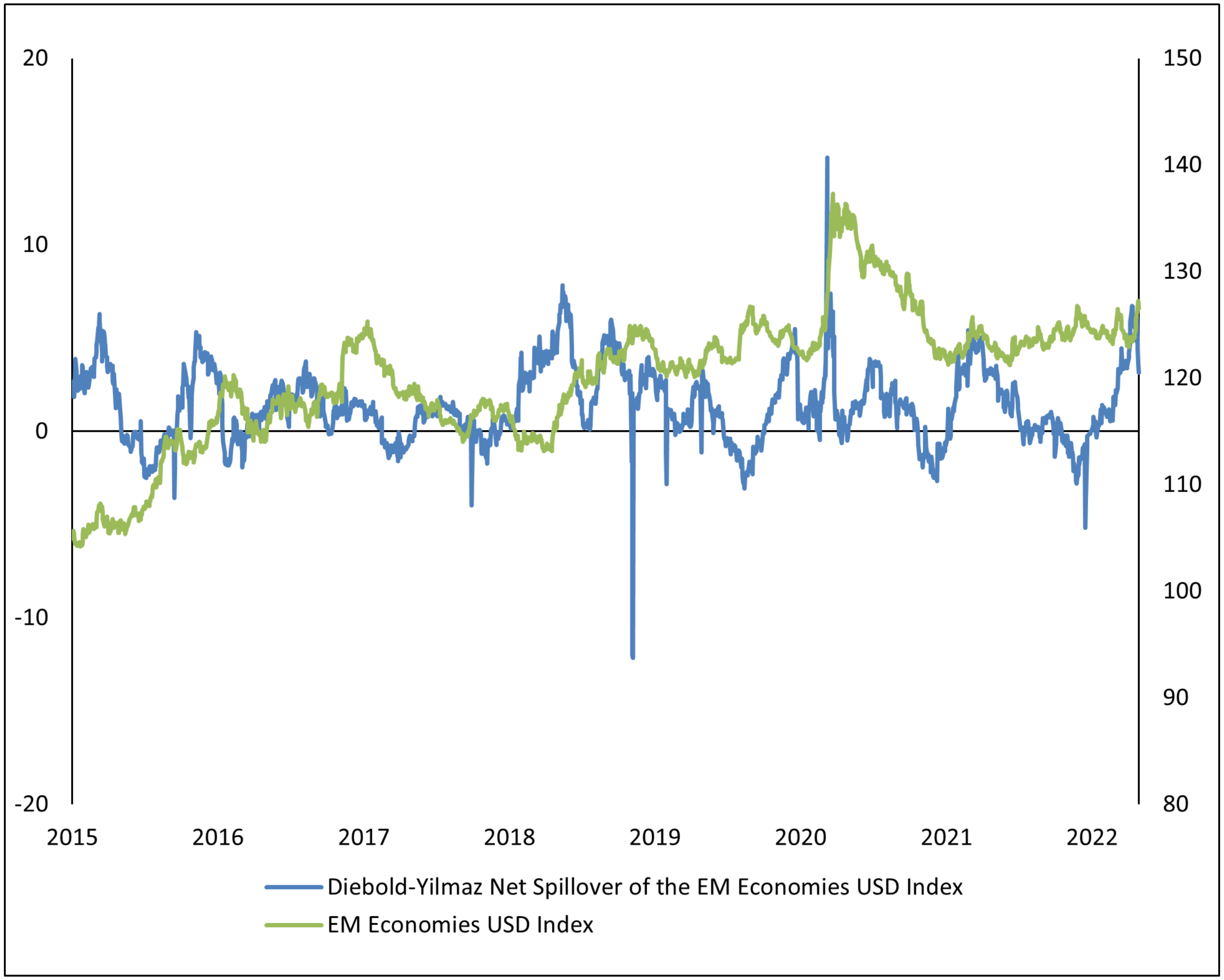
Figure 3: Diebold-Yilmaz net spillover of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio debt flows) and broad EM USD index: Main empirical results



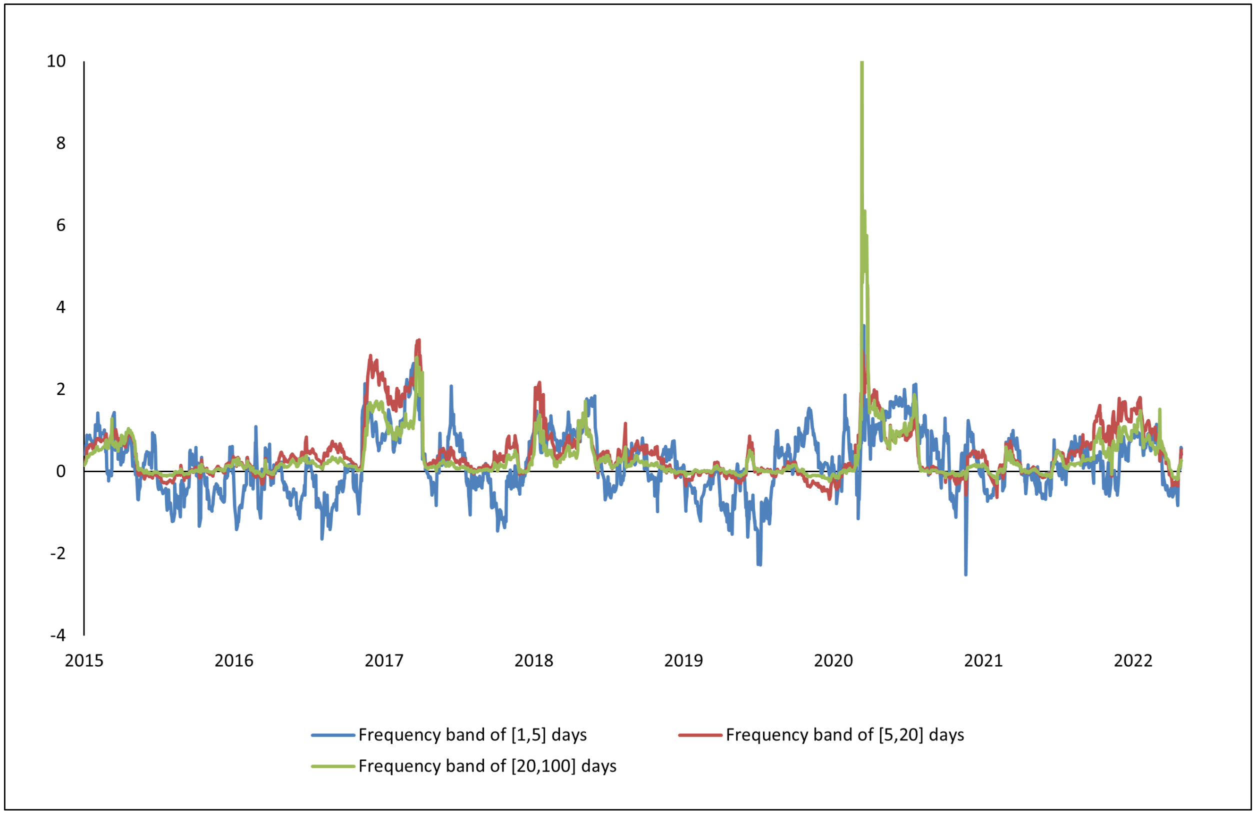
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio debt flows using the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM USD dollar exchange rate. The blue coloured line represents the net directional spillover index of the broad EM US dollar exchange rate (in log differences) (left-axis). The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with two lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure 4: Diebold-Yilmaz net spillover of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio equity flows) and broad EM USD index: Main empirical results



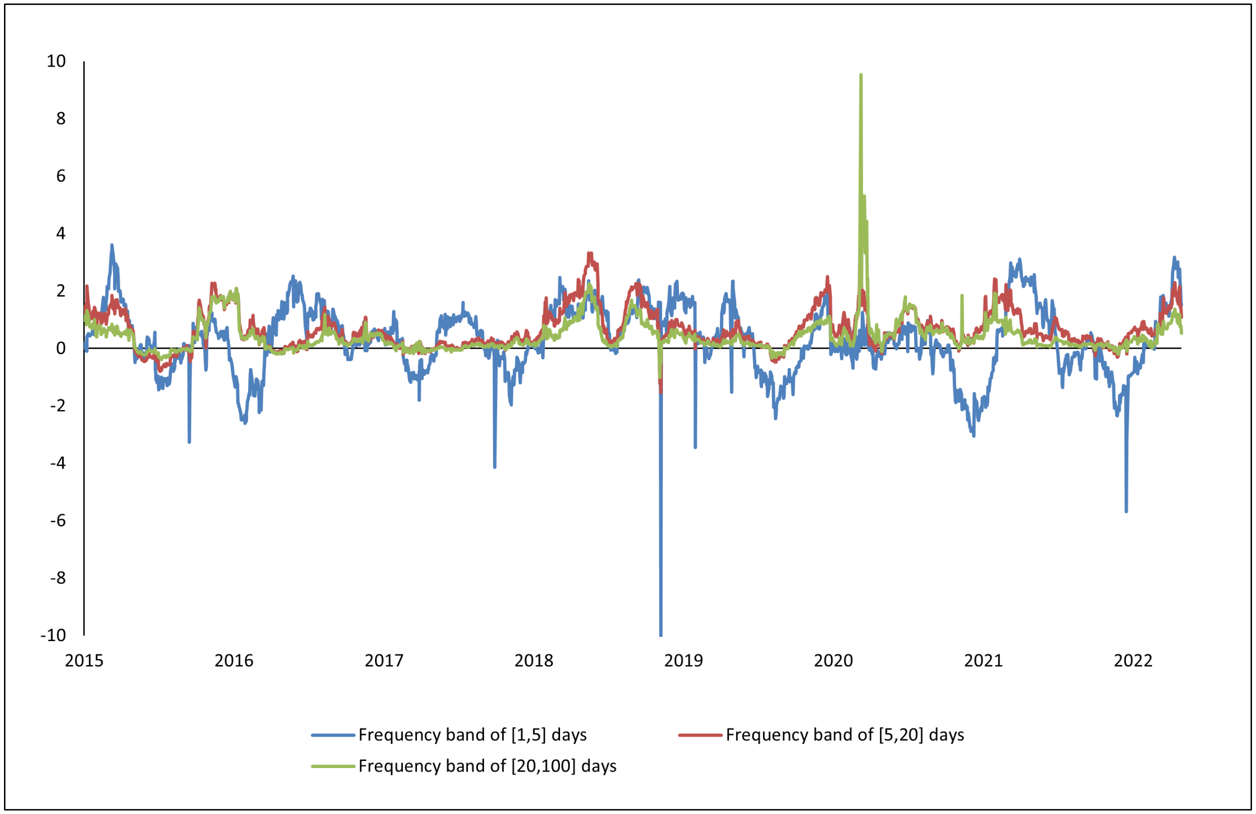
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio equity flows using the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM USD dollar exchange rate. The blue coloured line represents the net directional spillover index of the broad EM US dollar exchange rate (in log differences) (left-axis). The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with two lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure 5: Barunik-Krehlik net directional spillover across frequencies of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio debt flows): Main empirical results



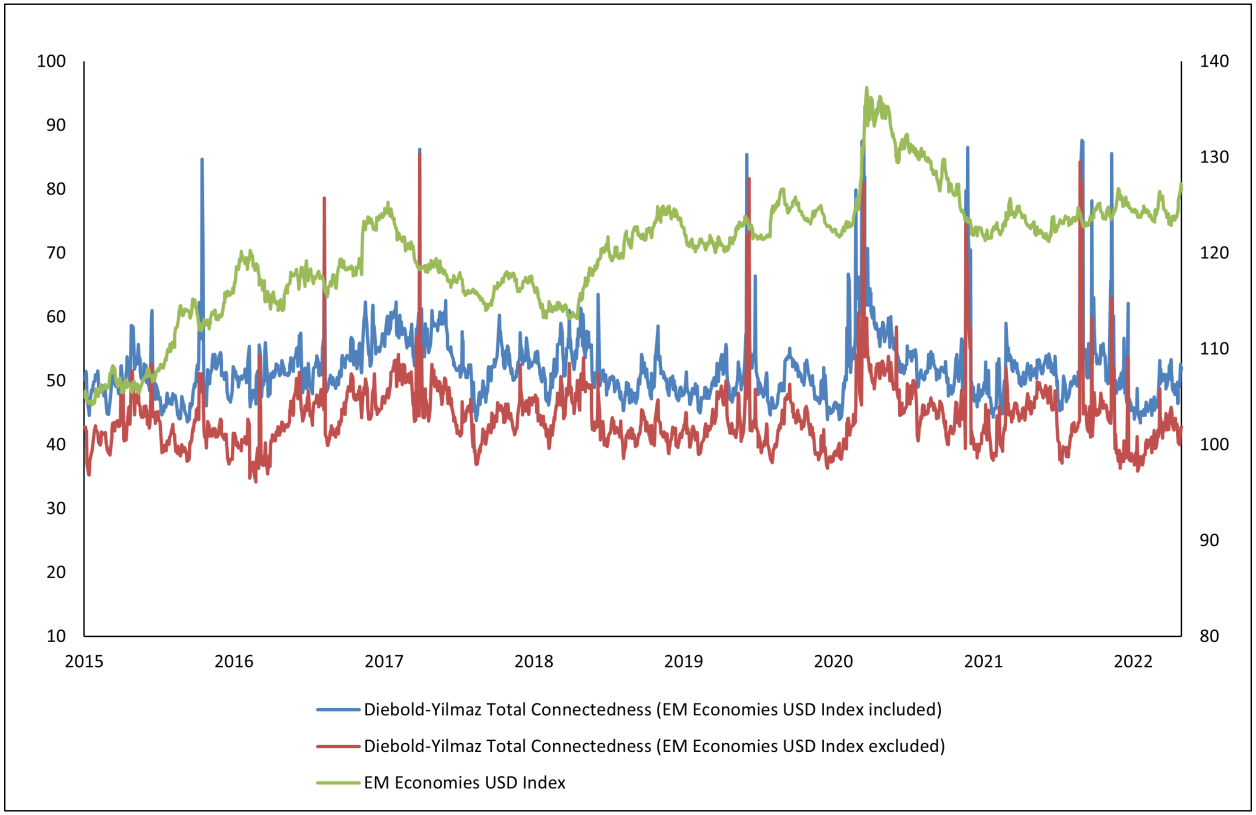
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio debt flows decomposed into the highest (short-term) (blue coloured line), intermediate (medium-term) (red coloured line) and lowest (long-term) (green coloured line) frequency bands using the Baruník and Křehlík (2018) framework. The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index decomposed into frequency bands come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with two lags.

Figure 6: Barunik-Krehlik net spillover across frequencies of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio equity flows): Main empirical results



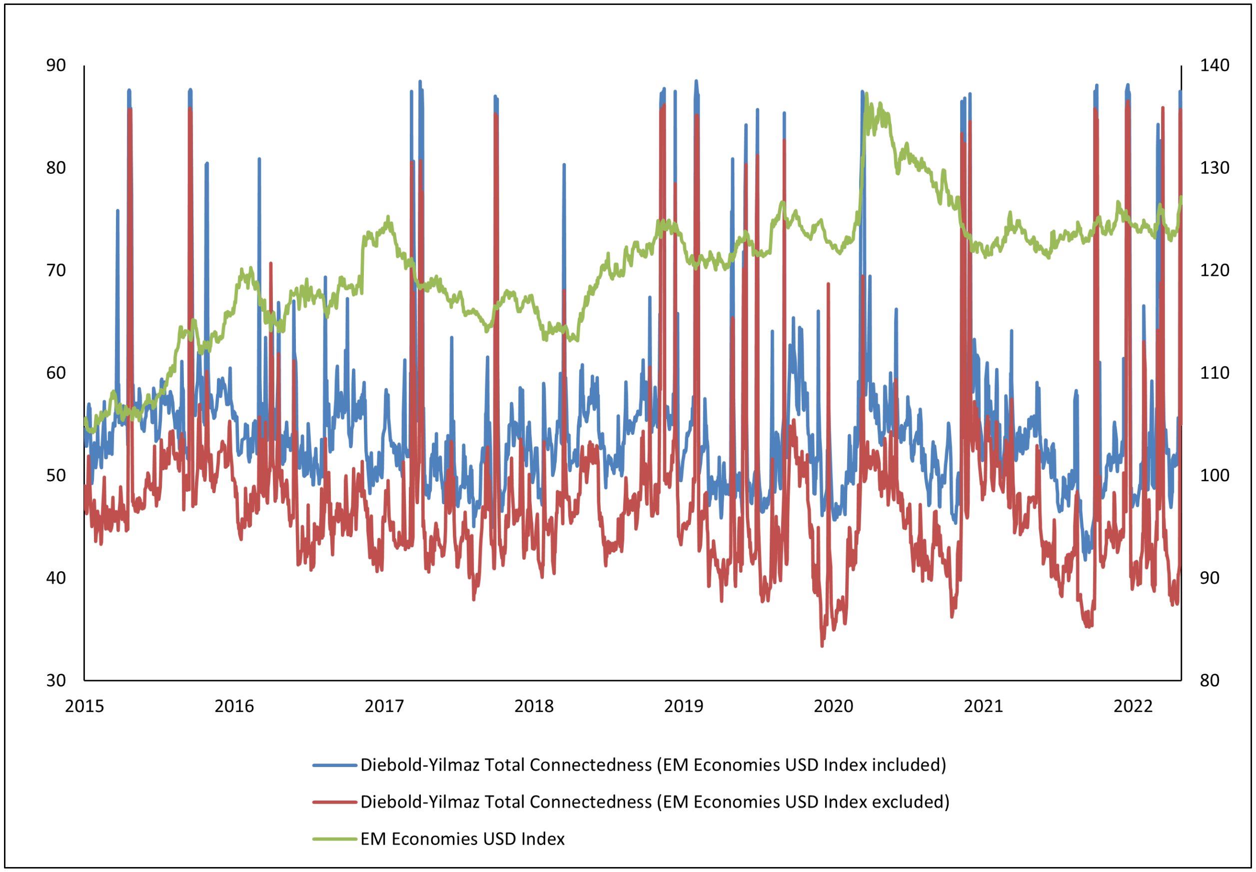
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio equity flows decomposed into the highest (short-term) (blue coloured line), intermediate (medium-term) (red coloured line) and lowest (long-term) (green coloured line) frequency bands using the Baruník and Křehlík (2018) framework. The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index decomposed into frequency bands come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with two lags.

Figure A1: Diebold-Yilmaz total connectedness index (daily net non-resident portfolio debt flows) and broad EM USD index: Robustness test I



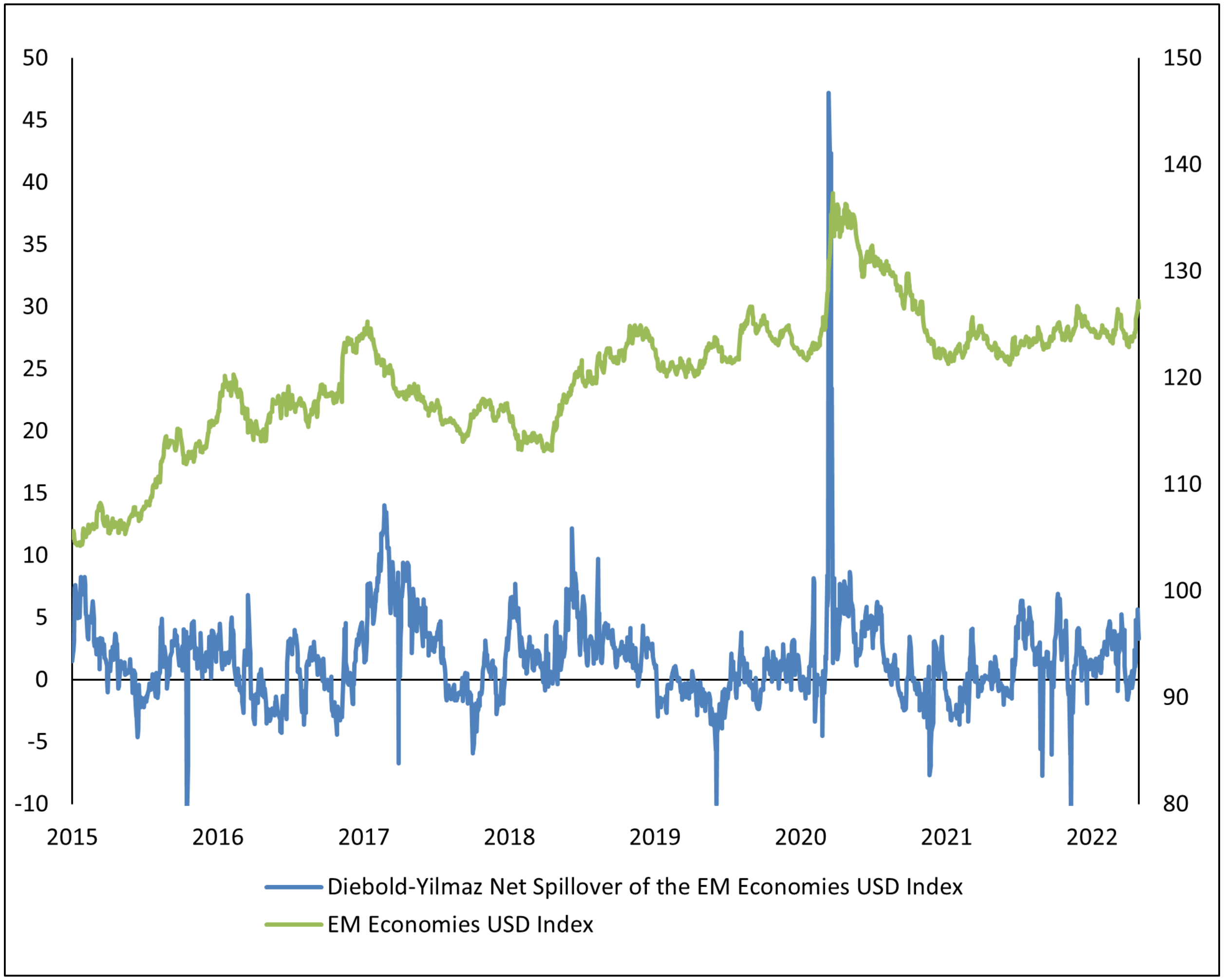
Notes: This figure displays the time-varying/dynamic estimates of connectedness based on the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM US dollar exchange rate. The red coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition where the endogenous variables are the individual EM economies' net non-resident portfolio debt flows (left axis). The blue coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition that includes the individual EM economies' net non-resident portfolio debt flows plus the broad EM US dollar exchange rate (in log differences) (left-axis). Both time-varying/dynamic estimates of connectedness are calculated from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with six lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A2: Diebold-Yilmaz total connectedness index (daily net non-resident portfolio equity flows) and broad EM USD index: Robustness test I



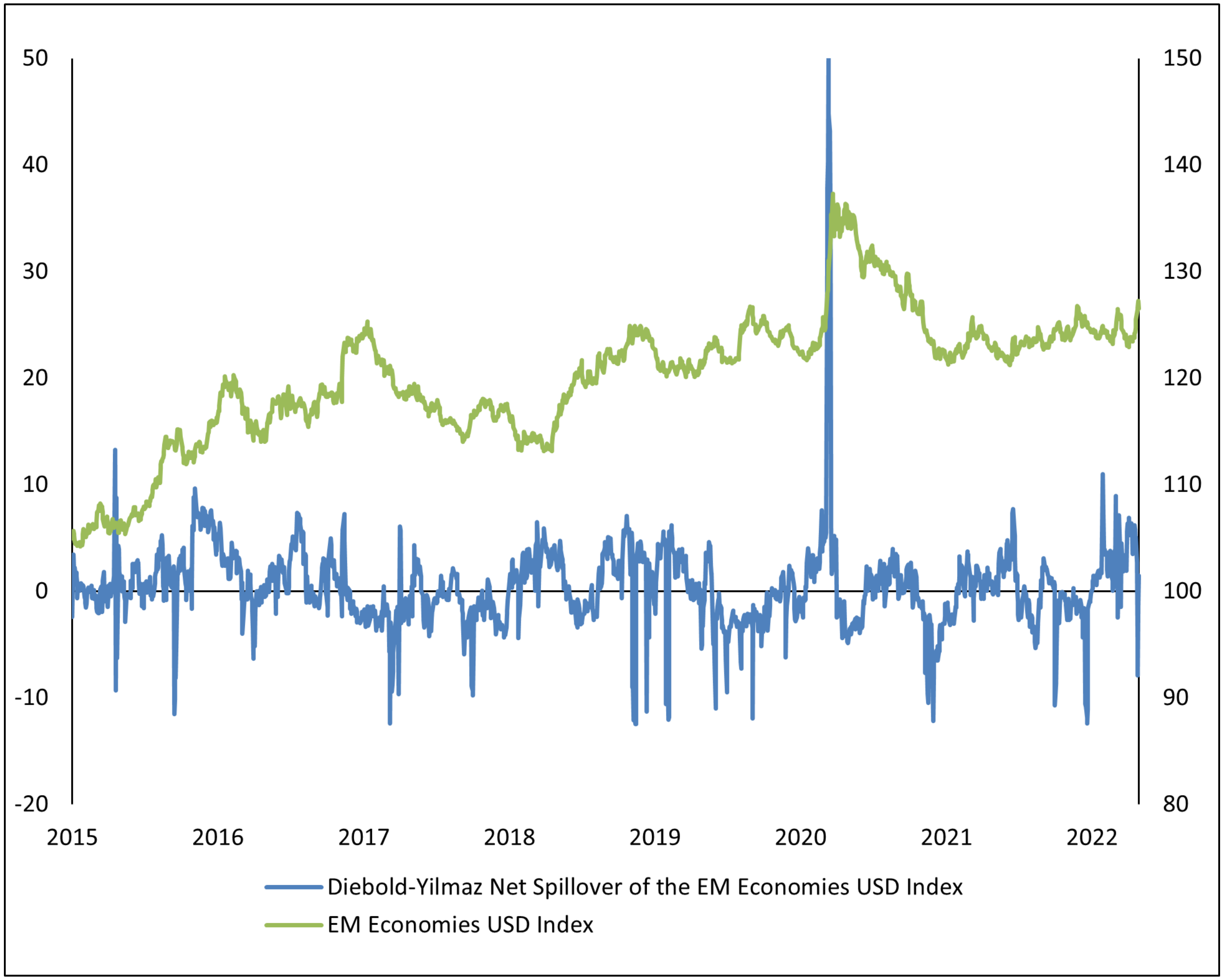
Notes: This figure displays the time-varying/dynamic estimates of connectedness based on the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM US dollar exchange rate. The red coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition where the endogenous variables are the individual EM economies' net non-resident portfolio equity flows (left axis). The blue coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition that includes the individual EM economies' net non-resident portfolio equity flows plus the broad EM US dollar exchange rate (in log differences) (left-axis). Both time-varying/dynamic estimates of connectedness are calculated from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with six lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A3: Diebold-Yilmaz net spillover of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio debt flows) and broad EM USD index: Robustness test I



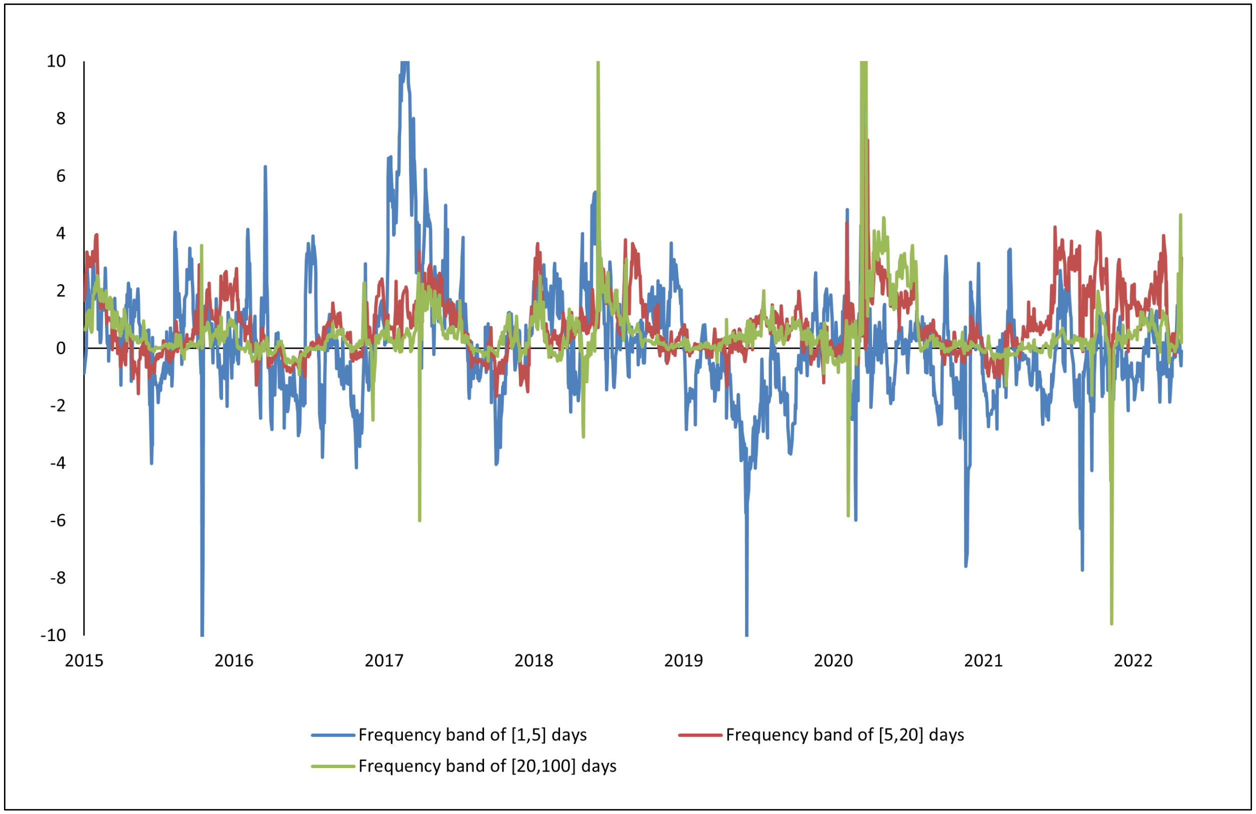
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio debt flows using the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM USD dollar exchange rate. The blue coloured line represents the net directional spillover index of the broad EM US dollar exchange rate (in log differences) (left-axis). The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with six lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A4: Diebold-Yilmaz net spillover of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio equity flows) and broad EM USD index: Robustness test I



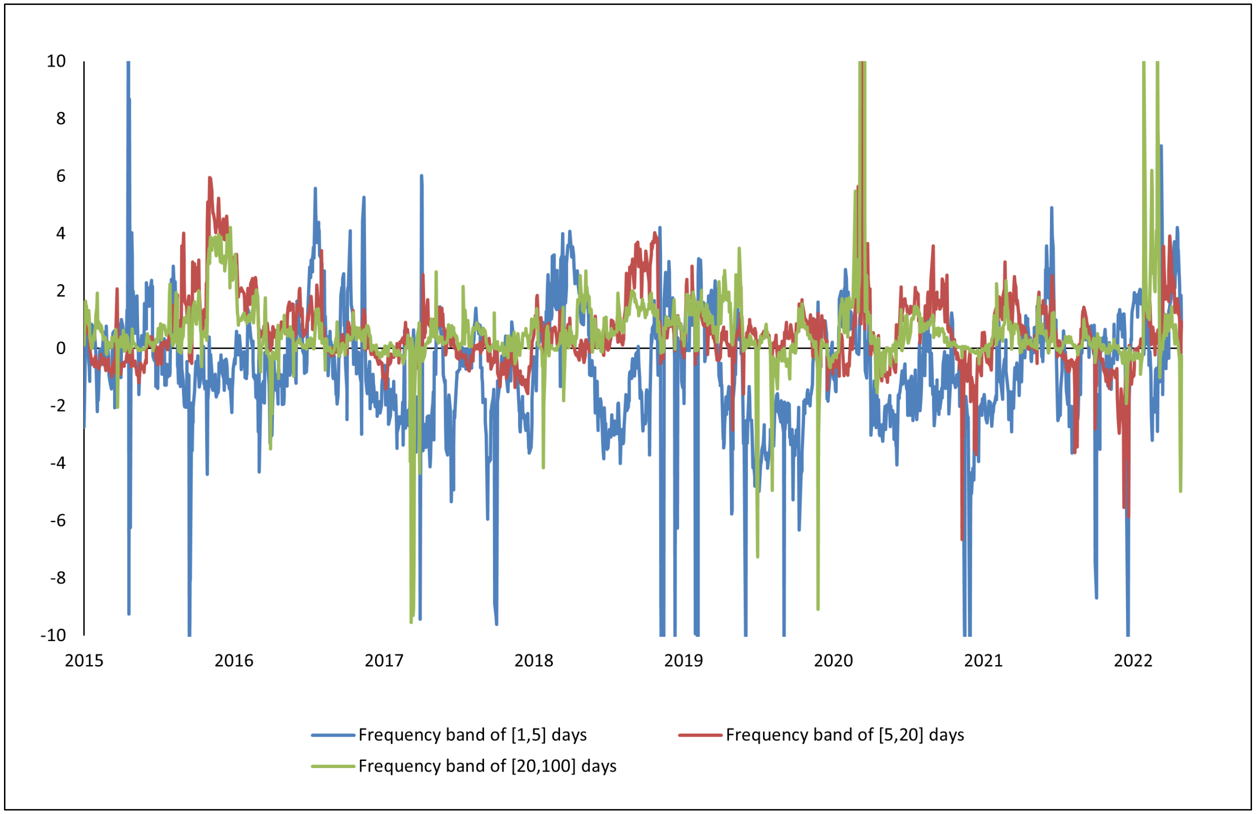
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio equity flows using the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM USD dollar exchange rate. The blue coloured line represents the net directional spillover index of the broad EM US dollar exchange rate (in log differences) (left-axis). The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with six lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A5: Barunik-Krehlik net directional spillover across frequencies of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio debt flows): Robustness test I



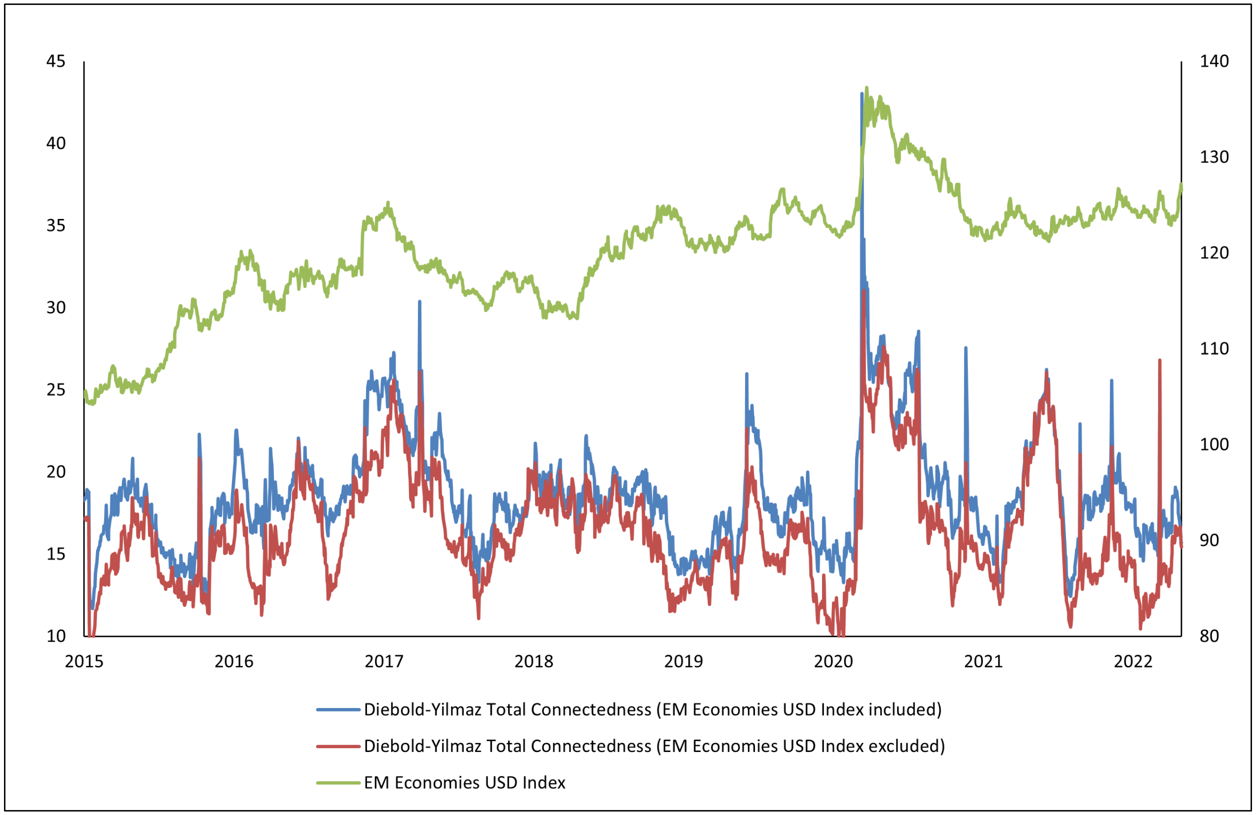
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio debt flows decomposed into the highest (short-term) (blue coloured line), intermediate (medium-term) (red coloured line) and lowest (long-term) (green coloured line) frequency bands using the Baruník and Křehlík (2018) framework. The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index decomposed into frequency bands come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ *days and from a VAR with six lags.*

Figure A6: Barunik-Krehlik net spillover across frequencies of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio equity flows): Robustness test I



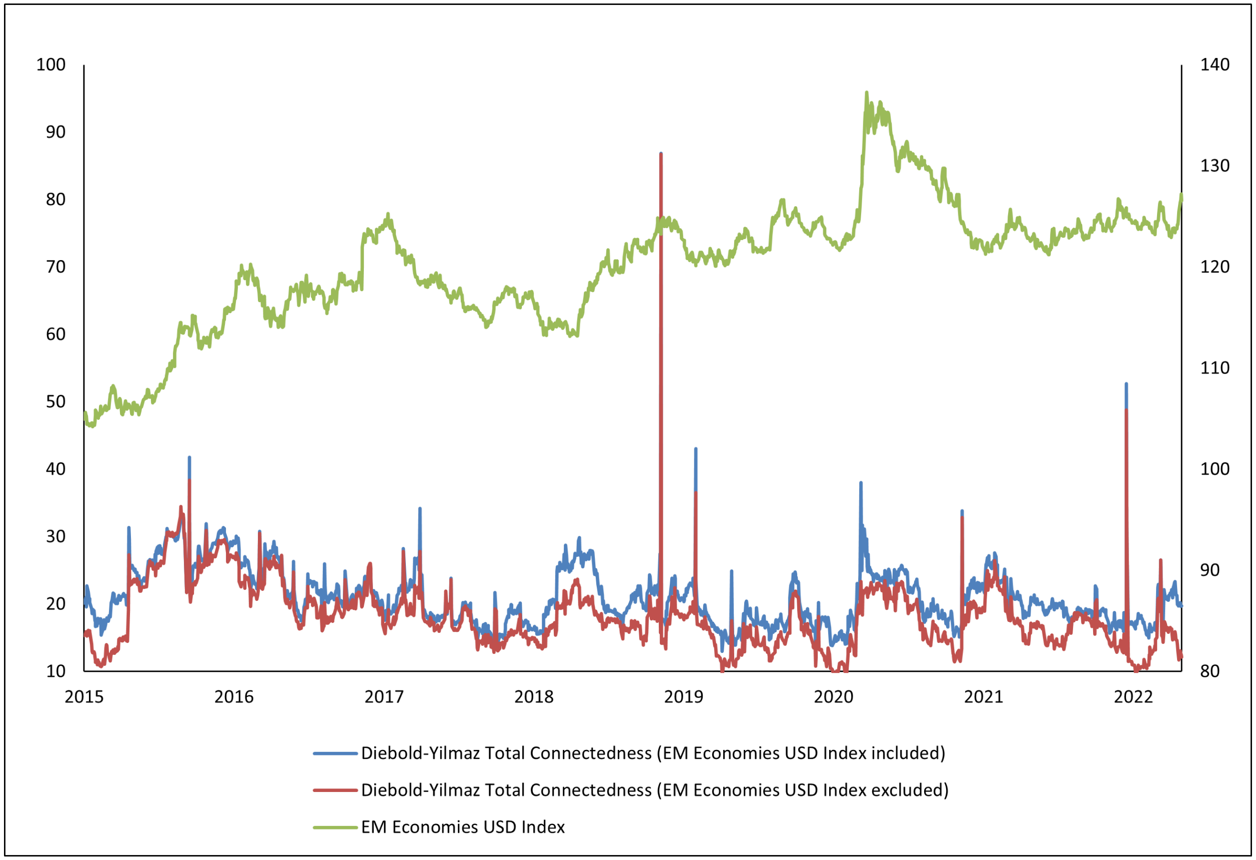
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio equity flows decomposed into the highest (short-term) (blue coloured line), intermediate (medium-term) (red coloured line) and lowest (long-term) (green coloured line) frequency bands using the Baruník and Křehlík (2018) framework. The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index decomposed into frequency bands come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 100$ days and from a VAR with six lags.

Figure A7: Diebold-Yilmaz total connectedness index (daily net non-resident portfolio debt flows) and broad EM USD index: Robustness test II



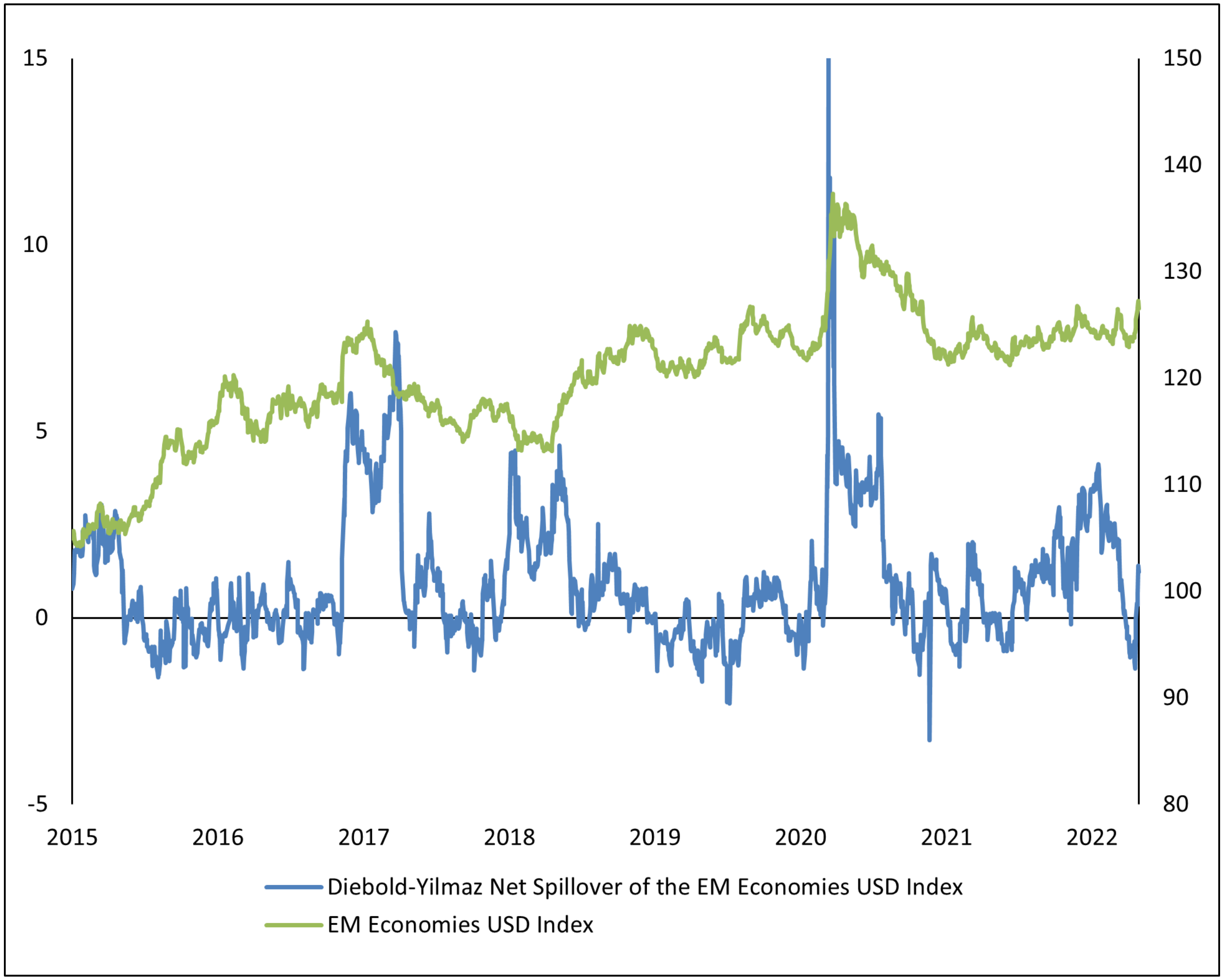
Notes: This figure displays the time-varying/dynamic estimates of connectedness based on the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM US dollar exchange rate. The red coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition where the endogenous variables are the individual EM economies' net non-resident portfolio debt flows (left axis). The blue coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition that includes the individual EM economies' net non-resident portfolio debt flows plus the broad EM US dollar exchange rate (in log differences) (left-axis). Both time-varying/dynamic estimates of connectedness are calculated from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 200$ days and from a VAR with two lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A8: Diebold-Yilmaz total connectedness index (daily net non-resident portfolio equity flows) and broad EM USD index: Robustness test II



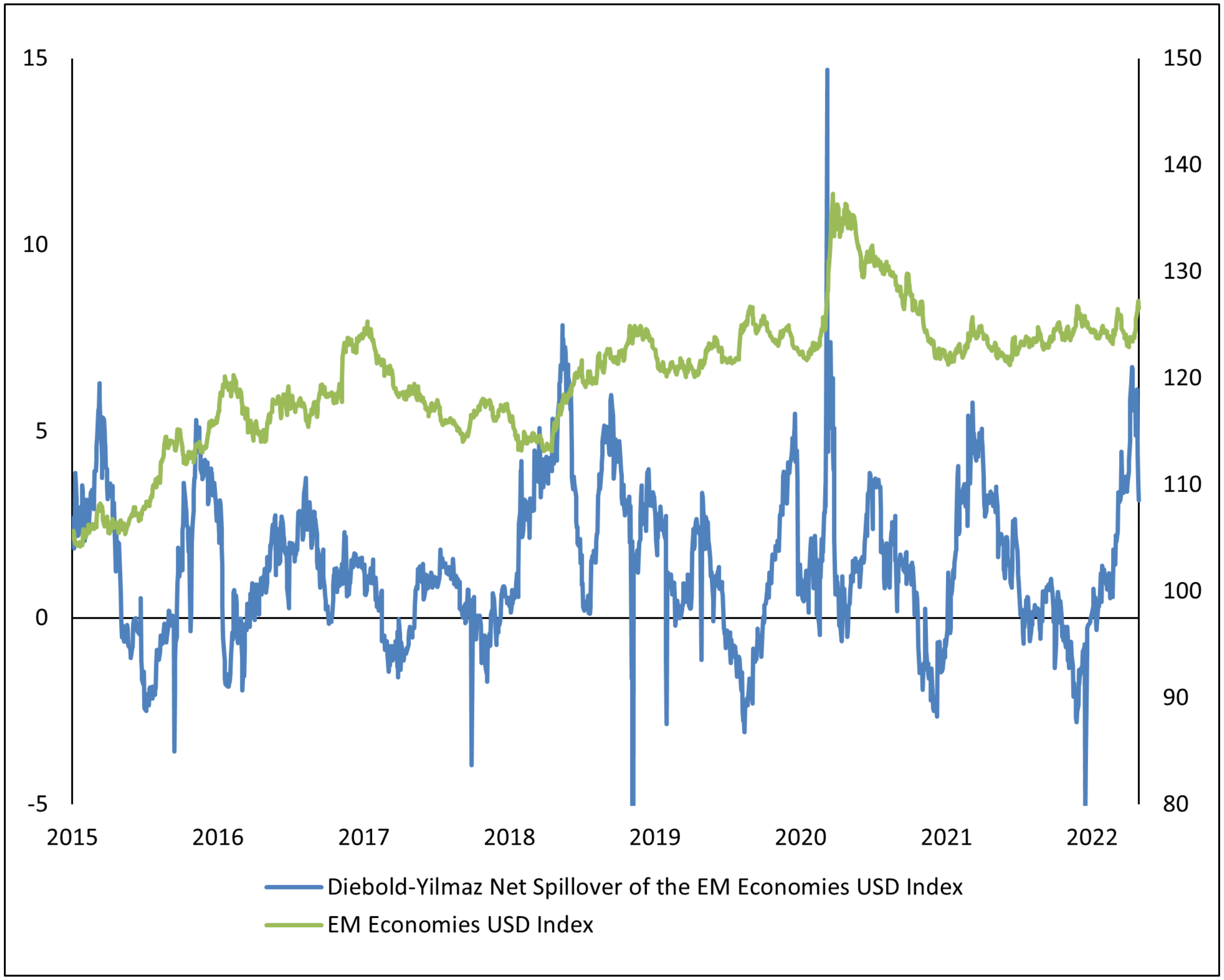
Notes: This figure displays the time-varying/dynamic estimates of connectedness based on the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM US dollar exchange rate. The red coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition where the endogenous variables are the individual EM economies' net non-resident portfolio equity flows (left axis). The blue coloured line represents the connectedness measures calculated from a generalised forecast error variance decomposition that includes the individual EM economies' net non-resident portfolio equity flows plus the broad EM US dollar exchange rate (in log differences) (left-axis). Both time-varying/dynamic estimates of connectedness are calculated from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 200$ days and from a VAR with two lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A9: Diebold-Yilmaz net spillover of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio debt flows) and broad EM USD index: Robustness test II



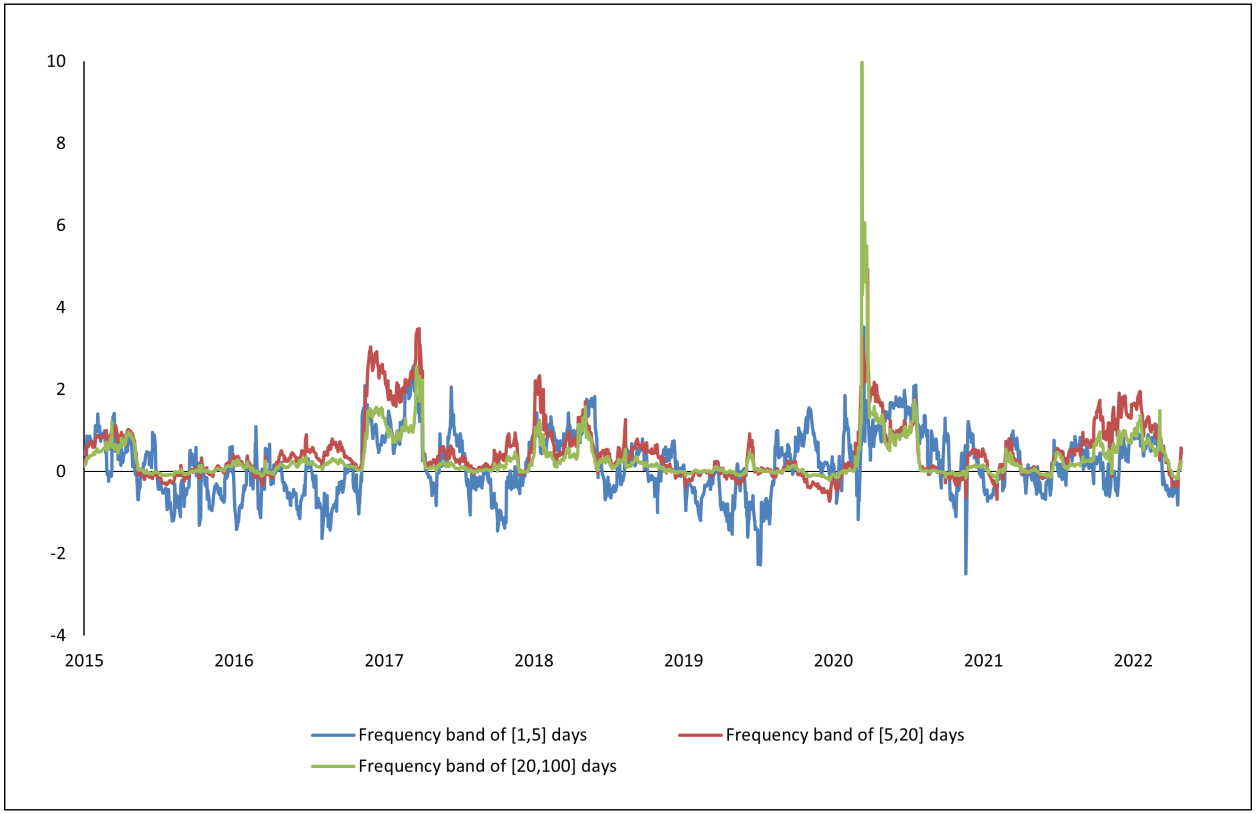
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio debt flows using the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM USD dollar exchange rate. The blue coloured line represents the net directional spillover index of the broad EM US dollar exchange rate (in log differences) (left-axis). The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 200$ days and from a VAR with two lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A10: Diebold-Yilmaz net spillover of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio equity flows) and broad EM USD index: Robustness test II



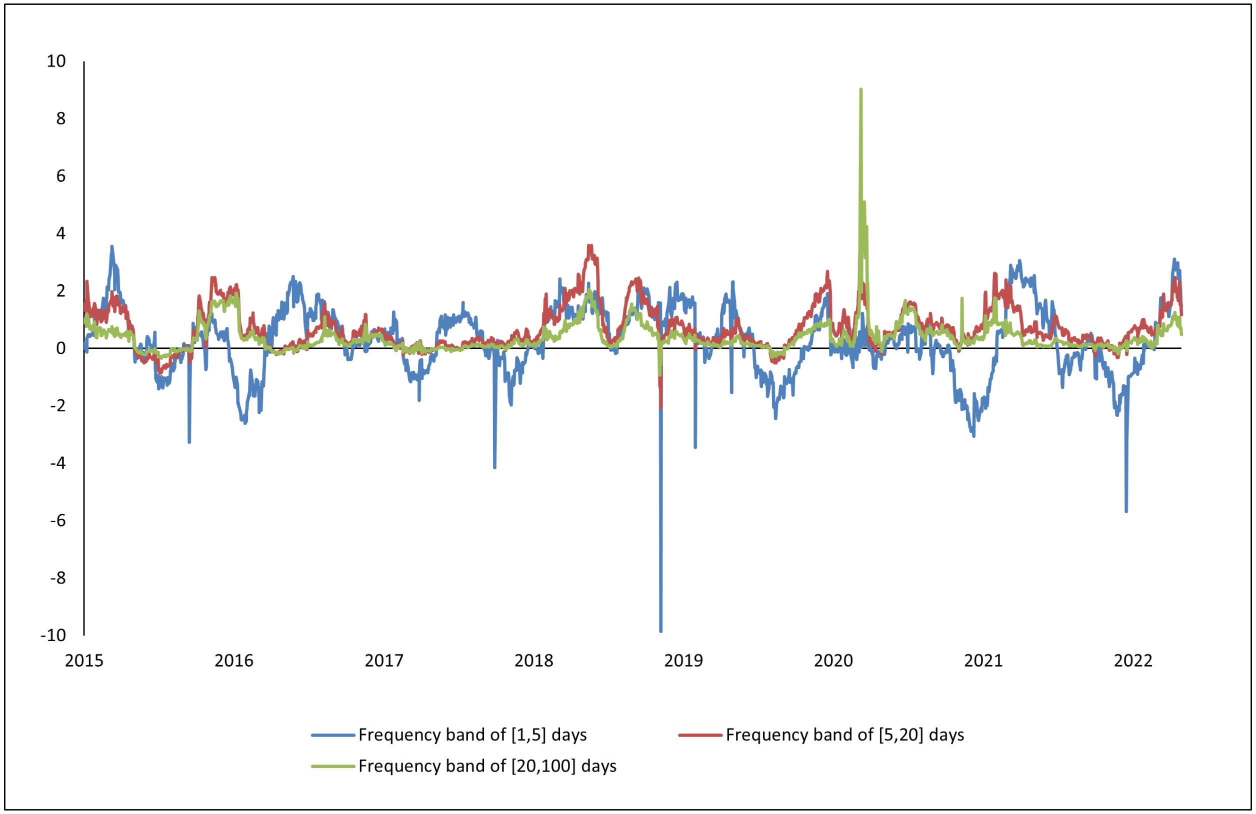
Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio equity flows using the Diebold and Yilmaz (2009, 2012, 2014) framework and the raw data on the broad EM USD dollar exchange rate. The blue coloured line represents the net directional spillover index of the broad EM US dollar exchange rate (in log differences) (left-axis). The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 200$ days and from a VAR with two lags. The green coloured line represents the raw data on the broad EM US dollar exchange rate (right-axis).

Figure A11: Barunik-Krehlik net directional spillover across frequencies of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio debt flows): Robustness test II



Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio debt flows decomposed into the highest (short-term) (blue coloured line), intermediate (medium-term) (red coloured line) and lowest (long-term) (green coloured line) frequency bands using the Baruník and Křehlík (2018) framework. The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index decomposed into frequency bands come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 200$ *days and from a VAR with two lags.*

Figure A12: Barunik-Krehlik net spillover across frequencies of the broad EM USD index to a selected group of EM economies (daily net non-resident portfolio equity flows): Robustness test II



Notes: This figure displays the net directional spillover index of the broad EM USD index (in log differences) to the EM economies' net non-resident portfolio equity flows decomposed into the highest (short-term) (blue coloured line), intermediate (medium-term) (red coloured line) and lowest (long-term) (green coloured line) frequency bands using the Baruník and Křehlík (2018) framework. The net directional spillover index is estimated by subtracting the directional "to" spillovers from the directional "from" spillovers. A net transmitter (receiver) of spillovers is identified when the spillover index is positive (negative). The time-varying/dynamic estimates of net directional spillover index decomposed into frequency bands come from the generalised forecast error variance decomposition using a rolling window size of 100 days, forecast horizon of $H = 200$ days and from a VAR with two lags.