HONG KONG INSTITUTE FOR MONETARY AND FINANCIAL RESEARCH

GAUGING DOLLAR FUNDING STRESS IN ADVANCED AND EMERGING MARKET ECONOMIES

Yuewen Tang and Alfred Wong

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Gauging Dollar Funding Stress in Advanced and Emerging Market Economies

Yuewen Tang
Hong Kong Monetary Authority

Alfred Wong
Hong Kong Institute for Monetary and Financial Research

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Abstract

We analyse dollar funding stress experienced by advanced and emerging market economies through studying the behaviour of their cross-currency bases vis-à-vis the US dollar. We find that except for a few advanced economy currencies, cross-currency bases are generally rather unconnected, especially at the shorter end of the market. The bases of emerging market economies are found to fluctuate a lot more and move in a more disorderly manner over time, as compared to those of advanced economies. Under extreme market conditions, emerging market economies also tend to be considerably more responsive in dollar funding stress to global financial volatility than advanced economies. Overall, the results suggest that more attention be paid to studying and monitoring the bases of emerging market currencies, given the potential implications for global financial stability.

* Email: Tang: ytang@hkma.gov.hk and Wong: alfred_yt_wong@hkma.gov.hk

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1. Introduction

The US dollar has played an unrivalled role in facilitating global trade and finance since a new international monetary order—in which major currencies were pegged to the US dollar which was in turn pegged to gold—was instituted in Bretton Woods in 1944. However, a noticeable decline in the share of the currency in world trade and global foreign reserves over the past two decades has stirred up heated debate about whether the currency can rise to the challenge in the 21st century.[1] More recently, the economic impact of the coronavirus pandemic has also renewed concerns about the future role of the US dollar as the leading reserve currency (Siripurapu, 2020).

An issue that has emerged in recent years is the problem of dollar funding shortage, a development attracting considerable international attention.[2] Since the global financial crisis in 2007/08, it has not been uncommon for non-US financial institutions to experience difficulties in obtaining dollar funding, especially in times of turbulent markets (Baba and Packer, 2009). The fact that dollar funding shortage or strains can often develop within a very short space of time poses significant risks to global financial stability, as the problem could reinforce the turmoil that financial markets already suffer during those tough times. Once again, the recent global health crisis perhaps provides the best testimony. In the beginning of the Covid-19 pandemic, when the rapid spread of the virus wreaked havoc on the global economy and dealt a big blow to international capital markets, dollar funding stress intensified sharply, causing additional turbulence to international funding networks (Avdjiev et al, 2020).[3]

In the media, the phenomenon of dollar funding stress, which is most easily observed in the cross-currency swap market, is often centred on how costly it is to obtain dollar funding using major currencies as collateral, especially the euro, the British pound and the Japanese yen (referred to as the G3 currencies hereafter). While these three currencies no doubt constitute the lion's share of the swap market trading globally, what happens to them may not reflect or indicate the level of stress experienced by non-G3 economies, in particular those in the emerging market world. However, given the interconnectedness of financial institutions and of financial systems, there could be important ramifications for the global economy as international financial crises have time

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[1] Data from the Society for Worldwide Interbank Financial Telecommunication show that the share of US dollar payment in global payments fell from around 50% at the turn of the century to below 40% in the beginning of 2021. According to the IMF's Currency Composition of Official Foreign Exchange Reserves survey, the last two decades also saw the share of US dollar assets in central bank reserves decline from around 70% to below 60%.

[2] The Committee on the Global Financial System commissioned a working group to investigate the phenomenon (Bank for International Settlements, 2020). The International Monetary Fund (2019) and Board of Governors of the Federal Reserve System (2021) also devoted substantial content of their recent financial stability reports to analysing the associated risks and vulnerabilities.

[3] In the end, the turmoil prompted the Federal Reserve to come to the rescue through enhancing existing swap line arrangements and establish new ones with other central banks.

and again proven that financial market stress can transcend national boundaries easily and rapidly.

In finance literature and policy forums, the focus is a little wider but still very much restricted to advanced economy currencies. It usually includes seven other advanced economy currencies in addition to the G3 (referred to as the G10 currencies hereafter) (Avdjiev et al, 2019; Cerutti et al, 2021).[4] Research aimed at studying emerging market currencies is sparingly seen. Moreover, most of the research is centred on explaining what causes or drives dollar funding stress to the economies concerned as a whole. There is a lack of analytical work on how much their stresses are related to each other and to what extent economies are affected individually to identify those that are more vulnerable and thus require help. However, this arguably concerns the policymaker more, given that the stress experienced by more badly hit economies could potentially trigger more widespread and severe turmoil in view of the highly interconnected nature of global financial markets today.

This paper seeks to contribute to the literature by comparing and contrasting the behaviours of the cross-currency bases around the world, in particular between those of advanced and emerging market economies. Given this objective, we aim to achieve the most comprehensive coverage possible. A total of 32 and 30 currencies vis-à-vis the US dollar are covered for the short and long-term markets respectively, which is essentially determined by data availability. As long as cross-currency swap trading exists for a currency vis-à-vis the US dollar, the currency is covered.

We analyse the cross-currency bases in two steps. First, we explore the interconnectedness of the bases by examining their correlations through clustering and studying their dynamics with the aid of time-varying correlation and statistical moment analysis. We find that the bases fall optimally into two clusters: one formed mainly by advanced economies and the other by emerging markets. In the former cluster, the bases of the G3 currencies are particularly closely knitted, with those of the currencies of a few small European nations having a strong tendency of tracking them. Outside this cluster, the bases of all other currencies are in general unconnected, especially at the short end of the market. We also find that the time-varying correlation is extremely low between the bases of advanced economies and emerging markets, while the statistical moment analysis reveals that the movements of the bases are significantly less synchronized among emerging markets than among advanced economies, though both groups of economies have generally found their bases moving more in tandem over time following the global financial crisis. All this suggests that research on dollar funding stress focused on advanced economy currencies can only tell part of the story.

[4] The seven other currencies are the Australian dollar, the Canadian dollar, the Danish krone, the New Zealand dollar, the Norwegian krone, the Swedish krona and the Swiss franc.

Second, we evaluate the behaviour of the cross-currency bases under extreme market conditions. We do so by estimating their response to global financial volatility individually. Our findings suggest that dollar funding stress is substantially more severe for emerging markets than for advanced economies during crisis times. The rate at which funding pressure intensifies in some emerging market economies under adverse market conditions is much faster than in advanced economies. Overall, the results suggest that more attention be paid to analysing and monitoring the bases of emerging markets, because not only do they behave very differently from those of advanced economies but they also tend to be more susceptible to adverse financial conditions.

The rest of the paper is organised as follows. Section 2 discusses the recent development of the cross-currency swap market, the rationale underlying the use of cross-currency swap bases as barometers of dollar funding stress, and the key statistical properties of the bases since the global financial crisis. In Section 3, given that dollar funding stress is widely viewed as a global phenomenon, we study whether cross-currency bases correlate with each other and if they do so more within their own group when classified between advanced and emerging market economies. We also evaluate how closely the bases of advanced or emerging market economies move together over time and among themselves within their own group. Section 4 then examines how the bases behave under various market conditions and which of them are more responsive to global financial volatility in times of adversity. Section 5 concludes our analysis with a brief discussion of the implications of our results.

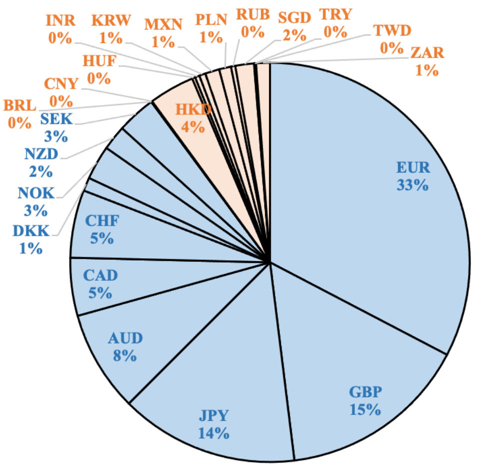
2. Overview of Cross-currency Swap Markets

Cross-currency swap markets can be looked upon as synthetic dollar funding markets. These markets are frequented by non-US financial institutions, especially when they find themselves shut out of the usual interbank money market. Since the global financial crisis, cross-currency swap transactions have experienced phenomenal growth. According to the Triennial Central Bank Survey of Foreign Exchange and Over-the-counter Derivatives Markets conducted by the Bank for International Settlements (BIS), average daily turnover almost doubled in the FX swap market between 2007 and 2019 and more than quadrupled in the cross-currency basis swap (CCBS) market (Figure 1).[5]

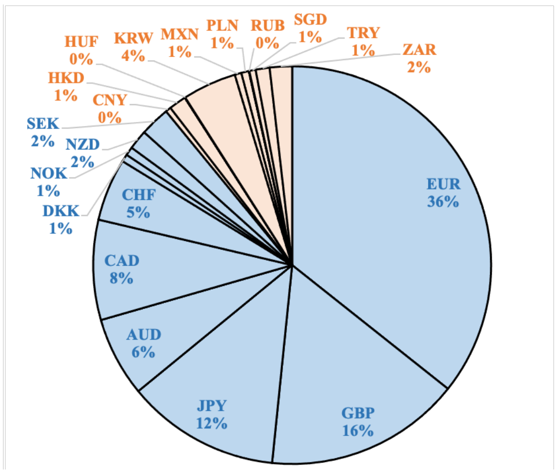
Figure 1 Currency market shares in the FX Swap and CCBS Markets*

FX Swap Market CCBS Market

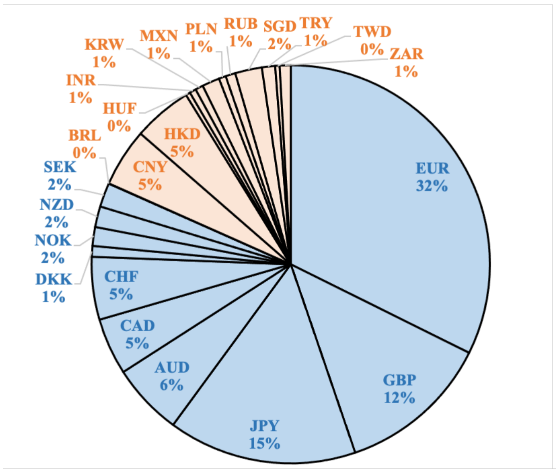
[5] The BIS Survey is conducted in April every three years with the latest one completed in 2019.



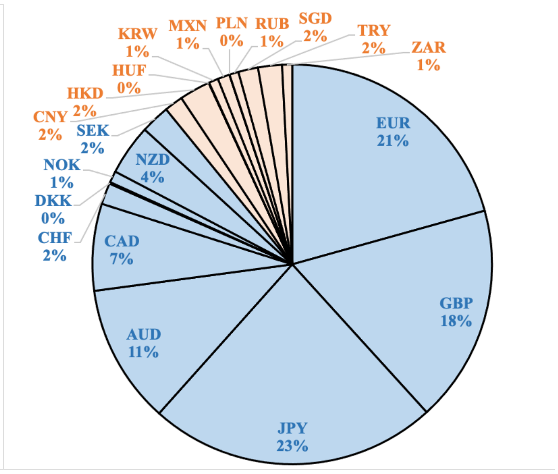
Average daily turnover: $1,484 billion
2007



Average daily turnover: $23 billion
2007



Average daily turnover: $2,828 billion
2019



Average daily turnover: $99 billion
2019

*The market shares are based on the turnover data for currencies vis-à-vis the US dollar in the BIS Triennial Central Bank Surveys. Currencies other than those shown in this chart are excluded due to lack of separate data reported.

Within the markets, trading involving emerging market currencies grew much faster. In the Surveys conducted in this period, transactions having a US dollar leg maintained a fairly stable proportion of about 90% of the total.[6] Figure 1 shows in pie charts the shares of the turnover of 23 and 20 currencies vis-à-vis the US dollar in the FX swap market and CCBS market respectively in 2007 and 2019.[7] Over this period, the G3 currencies declined slightly but still constituted the bulk of the market activity, accounting for about 60% in both FX swap and CCBS trading. Advanced economy currencies lost a significant market share to emerging market currencies in FX swap trading, which stood at

[6] For example, in 2019, the share of turnover that has a US dollar leg accounts for 91% and 94% of the FX swap market and CCBS market respectively. Hence, the share of turnover that does not involve the US dollar accounts for less than 10%.

[7] There are no separate figures for currencies other than these 23 and 20 currencies, but they account for a very small amount, e.g., 1.1% for the FX swap market in the 2019 BIS Survey.

18% at the end of the period. As the FX swap market is almost 30 times the size of the CCBS market, emerging market currencies have, overall, become much more important in the cross-currency swap market, even though there was little change in their share in CCBS trading.

Cross-currency bases, which are basically the prices in these synthetic dollar funding markets, are widely accepted yardsticks of dollar funding stress. In a nutshell, they represent the additional interest that one pays to borrow US dollars by pledging an equivalent amount of foreign currency as collateral. For short-term funding, this additional cost is commonly measured in terms of some benchmark US dollar interest rate *less* the implied US dollar interest rate in the FX swap market, which can be referred to as the FX swap basis.[8] For CCBS contracts, of which the maturity is usually one year or longer, the basis is directly traded on the market. Theoretically, under covered interest parity, as the interest differential between any two currencies is supposed to be offset by the forward premium/discount, cross-currency bases should not exist in the first place, at least not in a material way. The fact that they do in reality is often interpreted as reflecting the difficulty or stress on the part of the counterparty that borrows US dollars under disadvantaged terms.[9]

We have collected and computed the FX swap and CCBS bases vis-à-vis the US dollar for 32 and 30 currencies respectively from the beginning of 2007 to the end of the first quarter of 2021, mainly from Bloomberg and, for some currency pairs, also from various other sources.[10] The details and key descriptions of the data are given in Appendix A. We shall refer to the currency pairs as the currencies or their codes for brevity hereafter.

Based on how cross-currency bases are calculated and quoted in financial markets, most of them are negative but not always. They have fluctuated in a wide range from the onset of the global financial crisis: they can be very negative at certain times as well as very positive at other times.[11] Most of the bases are negative on average. Five out of 32 three-month bases and four out of the 30 five-year bases have a positive median. AUD, NZD and ZAR have a positive three-month as well as five-year median. The other two currencies that have a positive three-month median are COP and SGD, and the remaining currency that has a positive five-year median is CAD.

A popular explanation for the positive cross-currency bases is that the economies concerned have a net US dollar liability. Due to their usually tighter or less liquid domestic funding market, their financial institutions are often

[8] The implied US dollar interest rate is the foreign currency interest rate adjusted by the forward premium/discount, the difference between the spot and forward exchange rates.
[9] Such interpretation is not unanimous. See alternative explanations offered by Wong and Zhang (2018) and Bellrose and Norman (2019).
[10] We try to be as exhaustive as possible in our search for the data. We believe cross-currency markets for which we cannot find data are probably not active enough for the purpose of our study.
[11] The exceptions are ILS and MYR whose five-year bases have never traded above zero.

better off borrowing US dollars offshore and paying a basis to swap them into their own currency.[12] Hence, they are net suppliers of US dollars in the cross-currency swap market (Borio et al, 2016). This is in contrast with their counterparts in most other economies which need to fund their net US dollar asset position. Nonetheless, what is important is that the financial institutions of these economies would also come under pressure when dollar funding conditions tighten globally, as this implies that the cost of offshore funding is elevated. Indeed, when dollar funding stress heightened during the pandemic, the cross-currency basis of AUD fell, i.e., moving in the same direction as other cross-currency bases, as Australian banks cut back on their offshore funding activity (Reserve Bank of Australia, 2020). There are other explanations. For instance, Hutchison et al (2012) argue that capital controls of some emerging market economies such as China and India not only lead to a massive accumulation of official foreign exchange reserves but sometimes also create substantial positive cross-currency bases. In any event, since our analysis is focused on the changes or movements in cross-currency bases rather than their levels, whether they are positive or negative does not affect the conclusion of our study.

3. Interconnectedness of Dollar Funding Stresses

In this section we analyse how and to what extent cross-currency bases are connected with each other, and whether or not they are more so within certain groups, e.g., advanced and emerging market economies. We also investigate whether the bases of advanced economies fluctuate more than those of emerging markets do, and which group has a stronger tendency to co-move over time.

3.1 Clustering of correlations

We arrange the currencies according to their correlation coefficients (referred to as correlations for short hereafter) using hierarchical clustering order, a technique that builds a hierarchy of clusters in which objects in the same cluster are more similar to each other than to those in other clusters. The forming of the clusters is based on an algorithm that starts with each object being a cluster on its own and proceeds iteratively by combining two most similar clusters until all objects belong to only one cluster. Ward's minimum variance method is employed to determine which two clusters should be combined first in each step (Murtagh and Legendre, 2014). The silhouette coefficient is then computed to assess the optimal number of clusters (Rousseeuw, 1987). Appendix B provides the technical details about the clustering process.

[12] Australian banks, for instance, regularly fund their local AUD assets by tapping the more liquid US dollar funding markets overseas, e.g., issuing US dollar bonds.

Figure 2 presents the correlation matrices of the bases of various maturities arranged according to the order of leaves in the hierarchical clustering dendrogram.[13] The silhouette coefficients for each of the maturities suggest that the bases are in general clustered optimally into two groups such that the bases in the same group are most positively correlated with each other and at the same time most negatively correlated with those in the other group (Appendix B). The coefficient for the three-month basis is slightly in favour of a three-cluster outcome instead of a two-cluster, but not by much.

There are three characteristics about these matrices that are worth noting. The first and most striking of all is their colour. Given that dollar funding stress is a global phenomenon, one would expect that to a significant extent cross-currency bases tend to move in tandem such that the correlations between them are by and large positive. However, the dots are only marginally more blue than red, meaning that although the correlations are on average positive, the cross-currency bases do not really go hand-in-hand in general. Indeed, the frequency distributions of the correlations, for instance, for the three-month and five-year bases are right-skewed but only slightly, with 57% and 55% of the correlations being positive respectively (Appendix C).

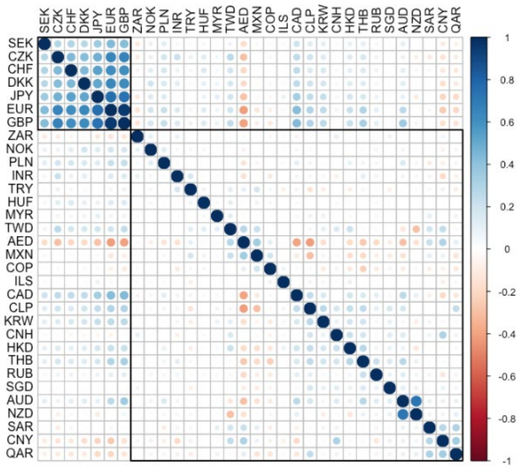
Second, the correlation between cross-currency bases is much stronger at the longer end of the funding market than at the shorter end. Regardless of whether the colour is blue or red, it is much darker, for instance, in the five-year matrix than in the three-month matrix, meaning that the stronger correlation holds true not only when it is positive but also when it is negative. The picture is also confirmed by the much flatter five-year frequency distribution compared to that of the three-month: 44% of the correlations fall within the range between -0.25 and 0.25 for the five-year bases compared to 77% for the three-month bases (Appendix C).

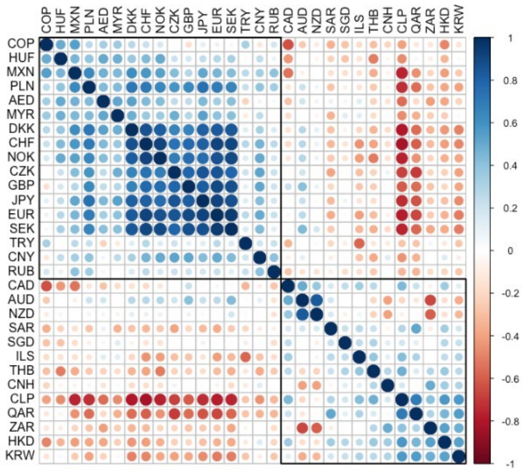
Figure 2 Correlation Matrices of Cross-currency Bases

1-month FX Swap Bases

1-year CCBS Bases

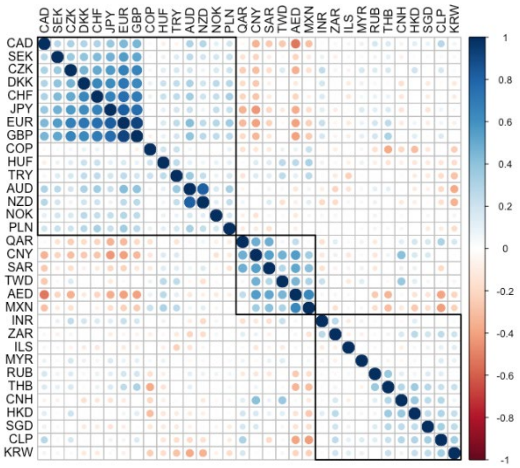
[13] A dendrogram is a binary tree plot that shows the hierarchical relationship between objects. It consists of various U-shaped lines that connect data points in a hierarchical tree. The last nodes of the hierarchy are called leaves. The dendrogram does not tell us the number of clusters which, however, is formed at a particular cluster cut-off value by drawing a line at that value and counting the number of branches of the tree that the line intersects.

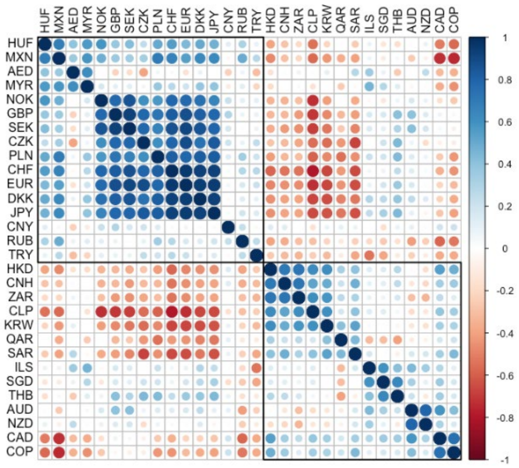




3-month FX Swap Bases

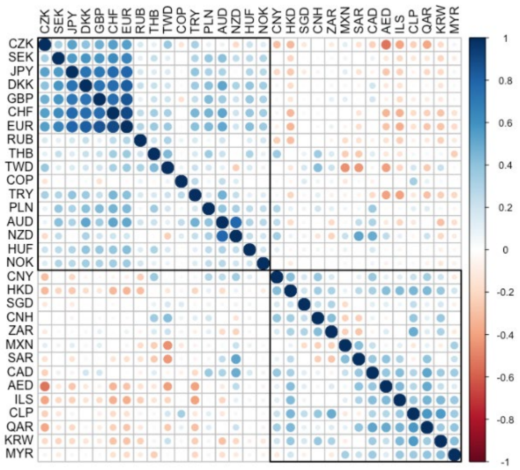
3-year CCBS Bases

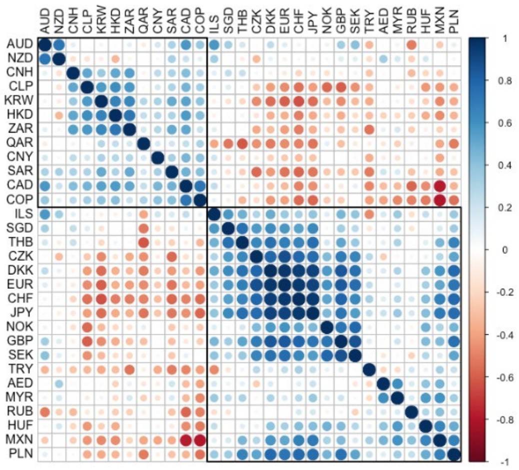




6-month FX Swap Bases

5-year CCBS Bases





Finally, the bases of only a small group of advanced economy currencies can be said to be truly interconnected. The G3 currencies stay very closely together across the maturity spectrum. The currencies of four smaller economies in Western Europe, namely, CHF, CZK, DKK and SEK, also have a strong tendency of co-moving with those of the G3. Parallel to this, there are seven currencies belonging to the other cluster across all the maturities, namely, CNH, CLP, HKD, KRW, QAR, SAR and ZAR but they are far less interconnected comparatively. Apart from these fourteen currencies, the rest are found in one cluster for some maturities but in the other cluster for other maturities. Judging from the brightness of the colour, the seven advanced economy currencies are always the darkest patch. The one-month matrix is perhaps most telling: the rest of the currencies are barely coloured. Moving from the short to the long end of the market, this advanced economy cluster expands with more currencies joining. However, while positive correlation increases between the currencies within the cluster, negative correlation also grows vis-à-vis those in the other cluster.

Hence, overall, the phenomenon of dollar funding stress is not really as global as it is often taken to be. Based on their correlations in the past decade or so, cross-currency bases are generally not interconnected. This is especially true at the shorter end of the market where the correlations are exceedingly low. The notable exceptions are the G3 currencies and to a lesser extent also some Western European currencies. At the longer end of the market, these advanced economies maintain strong positive correlations among themselves but at the same time their negative correlations with a number of emerging market currencies also become more elevated. All this suggests that it is important that more efforts be devoted to understanding the behaviour of cross-currency bases in the emerging market world in studying this so-called global problem.

3.2 Dynamic correlations of cross-currency bases

The correlations take a snapshot of the relationships between the bases over the sample period. To gauge how and how much they move in relation to each other over time, we employ two separate tools, the time-varying correlation and statistical moments, to analyse the relationship of the bases between the advanced and emerging market economies and within the two groups over time.

Time-varying correlation

We first calculate the weighted average cross-currency basis of advanced economies and of emerging market economies, using the turnover data compiled in the BIS Survey as weights.[14] In doing so, we classify the G10

[14] The BIS also publishes biannual data on the notional amount and gross market value of FX derivatives. However, the breakdowns of these data are available for only six currencies (in addition to the US dollar). Another problem is that the FX swap and outright forward data are not separated.

currencies under advanced economies and the non-G10 under emerging market economies, which is to a large extent consistent with the results of the clustering analysis, although there is admittedly no perfect way of dividing the world between advanced and emerging market economies.[15] To save repetition, we focus on the three-month FX swap and five-year CCBS bases which are commonly used to represent the short and long-term markets in the literature. To take into account the changing market shares of the currencies in this period, we adopt a varying weight approach to the calculation instead of employing fixed weights based on the turnover of the last Survey or the average turnover of all the Surveys.[16]

As can be seen in Figure 3, the average cross-currency basis of the emerging market economies fluctuates a lot more than that of the advanced economies. The figure also shows that the former generally suffers greater dollar funding stress, with a more negative average basis, except for the second half of the sample period in the short-term market, especially between 2005 and 2007. It is tempting to attribute the larger and greater variability of the basis to structural reasons. For instance, Hutchison et al (2012) argue that these could be a result of no-arbitrage bounds in the presence of capital controls and market illiquidity. However, this is hardly conclusive. Like the bases of advanced economy currencies, those of emerging market currencies were also practically non-existent when market forces governed by covered interest parity worked smoothly before the GFC. Therefore, as structural forces did not play a role in preventing market forces from working before the GFC, there seem to be no convincing reasons that they now do.

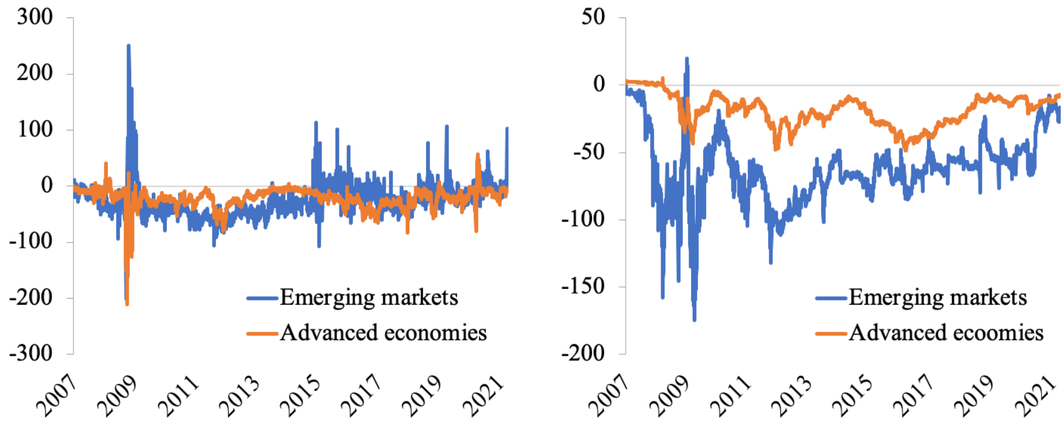
Figure 3 Turnover-weighted Average Cross-currency Bases

3-month FX Swap Bases | 5-year CCBS Bases

Moreover, the notional amount and gross market value data for each currency are reported on an aggregate basis (i.e., vis-a-vis all other currencies) and there are no breakdowns specifically with respect to the US dollar. Nonetheless, when we compare the weights based on market turnover on an aggregate basis with those based on notional amount or gross market value, we find that they are fairly comparable. Hence, the weights based on market turnover vis-a-vis only the US dollar are unlikely to be significantly different from those based on notional amount or gross market value, even if the latter set of data is available.

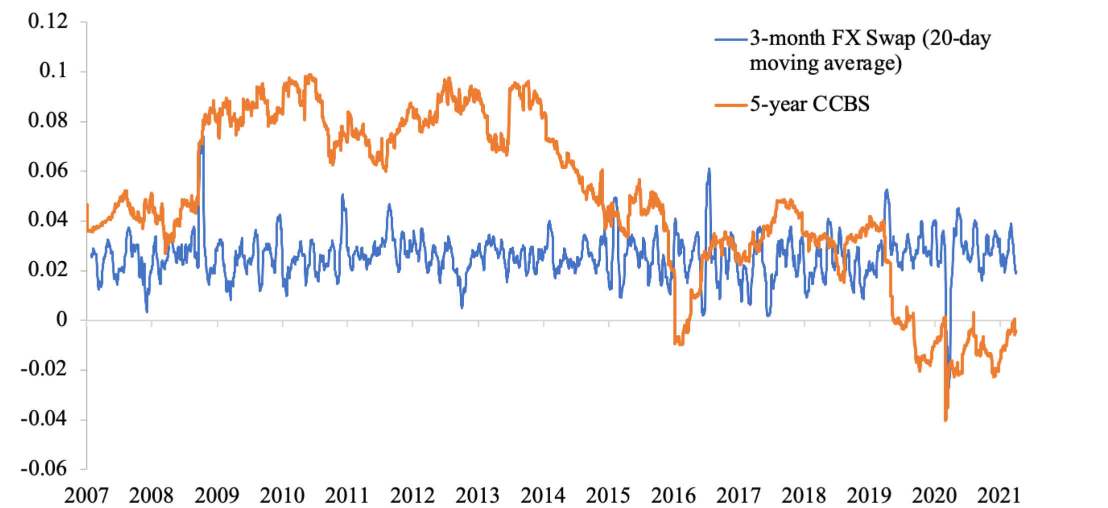
[15] Another reason we employ this classification is that many previous studies focus on the G10 currency pairs, so this can allow us to compare the properties of their bases with those of other currencies.

[16] The daily market turnover in each Survey is taken as that on 16 April of the year in which the Survey was conducted. The data are then interpolated and extrapolated on a cubic spline basis to cover the whole period before the weights are constructed.



Next, we estimate the time varying correlation between the bases of advanced and emerging markets by means of dynamic conditional correlation (DCC) pioneered by Engle and Sheppard (2001).[17] Figure 4 shows the DCC of the three-month and five-year bases between advanced and emerging market economies from January 2007 to March 2021. As can be seen, both exhibit an extremely low, though positive, correlation. The correlation of the three-month bases was very steady, fluctuating around 0.02 throughout the whole period, whereas that of the five-year bases edged up to between 0.06 and 0.10 shortly after the global financial crisis in the first half of the period but gradually declined to practically zero in the second half or even slightly negatively towards the end.

Figure 4 Dynamic Conditional Correlations of Cross-currency Bases between Advanced Economies and Emerging Market Economies



[17] Instead of modelling a time-invariant conditional covariance matrix, this model is based on the covariance matrix that can be decomposed into conditional standard deviations and a correlation matrix, which are both designed to be time-varying.

Divisia moments

We employ the Divisia (1925/1926) moments to analyse the changes in relative cross-currency bases. A Divisia index is a theoretical construct for compiling an index of continuous-time changes in the components of an aggregate. Diewert (1976) defines the class of superlative index numbers and shows that the Törnqvist (1936) discrete time approximation to the continuous-time Divisia index could provide a second order approximation to any true aggregate.[18] In the Törnqvist procedure, the change is the weighted average of the logarithmic changes between consecutive observations of the components, with the weights being the simple average of the shares of the components in the corresponding pair of periods.

Since logarithmic changes are essentially percentage changes and cross currency bases are measured in percentage, we simply take the first difference of the data instead. Therefore, the Divisia cross-currency basis index can be defined as the weighted average of changes in cross-currency bases,

$$DI_t = \sum_{i=1}^{n} \omega_{it} \Delta Basis_{it}$$

where ω_{it} is the average share of the market turnover of currency *i* vis-à-vis the US dollar in the market turnover of all currencies between time *t-1* and time *t*; and $\Delta Basis_{it}$ is the change in cross-currency basis *i* from time *t-1* to time *t*. The Divisia index can be interpreted as a first-order moment. The corresponding second-order moment is the Divisia cross-currency basis variance,

$$DV_t = \sum_{i=1}^{n} \omega_{it} (\Delta Basis_{it} - DI_t)^2$$

which is the weighted average of squared differences of changes in individual cross-currency bases from the Divisia index. Hence, the Divisia variance can provide a succinct aggregate measure of the extent to which the bases move relative to one another over time. In other words, it measures the time-varying dispersion of changes in the bases or, simply put, how disproportionately they change over time. The Divisia variance rises when cross-currency bases tend to change in a chaotic manner and falls when they move in tandem. If the change in the basis is the same across all currencies, it vanishes.

[18] A superlative index refers to one that can approximate any smooth economic function in which a small change in one variable is related to a corresponding change in another variable, e.g., the price-quantity relationship in the demand function. For instance, given a change in the price and the resulting quantity response, the level of the superlative index will change exactly as much as the change in demand.

Figure 5 shows the scatterplots of the Divisia index of the advanced economies against that of the emerging markets. From the relative scale of the axes of these scatterplots, one can see that the emerging market bases fluctuate a lot more than their advanced economy counterparts. And there is hardly any relationship between them, a result that agrees well with that of the DCC. Figure 6 charts the Divisia variances of the advanced and emerging market economies. As can be seen, they both present a similar picture in which the movements of the bases within their own group have generally become more in sync in both the short-term and long-term markets over the past decade or so, despite a pickup towards the end. Relatively speaking, the emerging market bases move much more disproportionately than the advanced economy bases.

Figure 5 Divisia Cross-currency Basis Indices

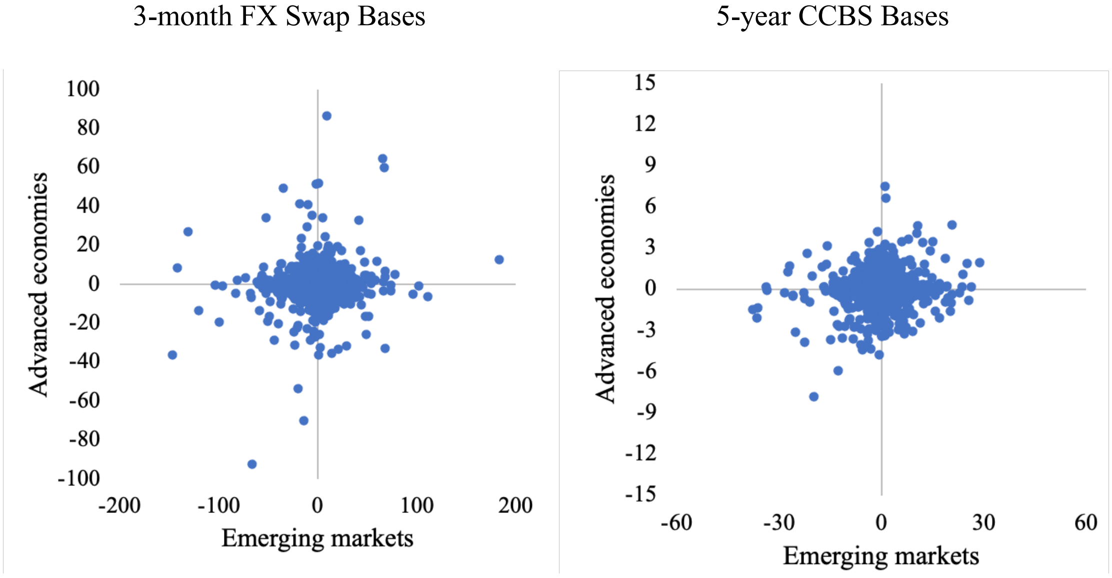
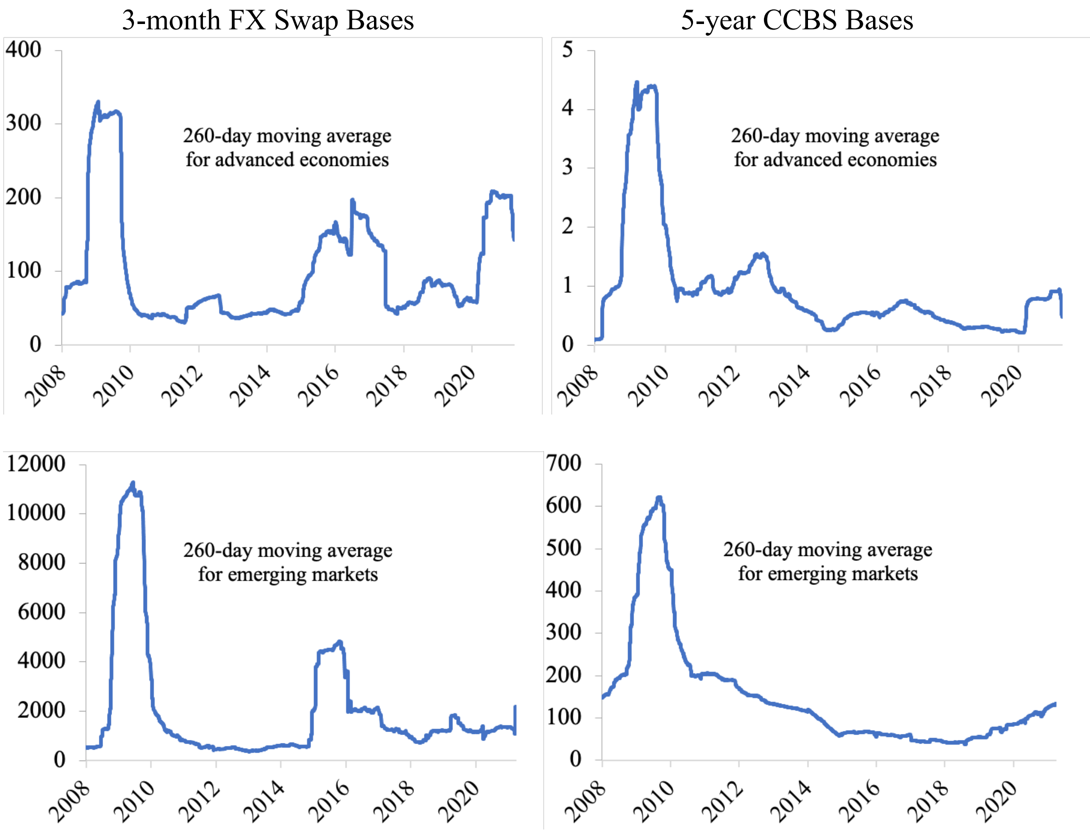


Figure 6 Divisia Cross-currency Basis Variances



4. Dollar Funding Stress under Extreme Market Conditions

In this section we analyse how dollar funding stress behaves across different currencies under extreme market conditions. This is probably most important to the policymaker as it is where vulnerabilities lie.

4.1 Technique and model

To do so, we employ the technique of quantile regression (QR), which adopts a simple non-parametric approach first advocated by Koenker and Bassett (1978), given its many advantages in analysing relationships between variables under extreme market scenarios.[19] The method of ordinary least squares (OLS) is about finding the average relationship between the dependent and independent variables over the sample period. The problem is that a reasonably large sample probably encompasses long periods of time characterized by a fairly orderly or uneventful market, which can bury or dilute the relationship of interest. Good times and bad times may also cancel out each other's effect on the dependent variable. Hence, using OLS, one may not be able to detect any relationship at all.

In light of this, some economists resort to separating the sample into crisis and non-crisis periods (e.g., Cerutti et al, 2021). However, this approach entails defining the periods, which differ from one country to another. Even for crises that impact the global economy, they often begin and end at different times for different countries, let alone those crises that occur at the regional or country level. Setting a uniform period for all may be acceptable for analysing a small close-knit group of economies but is far from ideal for studies with a broad or global coverage such as ours. In this connection, the technique of QR reigns supreme as there is no need to define crisis and non-crisis periods. Instead, it lets the data determine what is most relevant for the economy concerned.

In addition to being more effective in detecting the underlying relationships of interest, QR offers greater robustness against outliers of the dependent variable and higher efficiency than OLS over various non-normal error distributions.[20] The reason is that the sample mean can be easily affected even by a single observation when it is sufficiently far from the rest. However, in QR, an asymmetrically weighted sum of absolute errors, rather than the sum of squared errors in the case of OLS, is minimised for each conditional quantile function, so that the effect of distant observations on the sample median or other quantiles is lessened regardless of how far the outlier lies. Thus, QR estimates are more robust to outlying observations with large residuals.

[19] The technique has recently gained increasing popularity for estimating a variety of extreme market situations in finance literature (e.g., Brunnermeier et al, 2008; Fong and Wong, 2012; Ma and Pohlman, 2008).

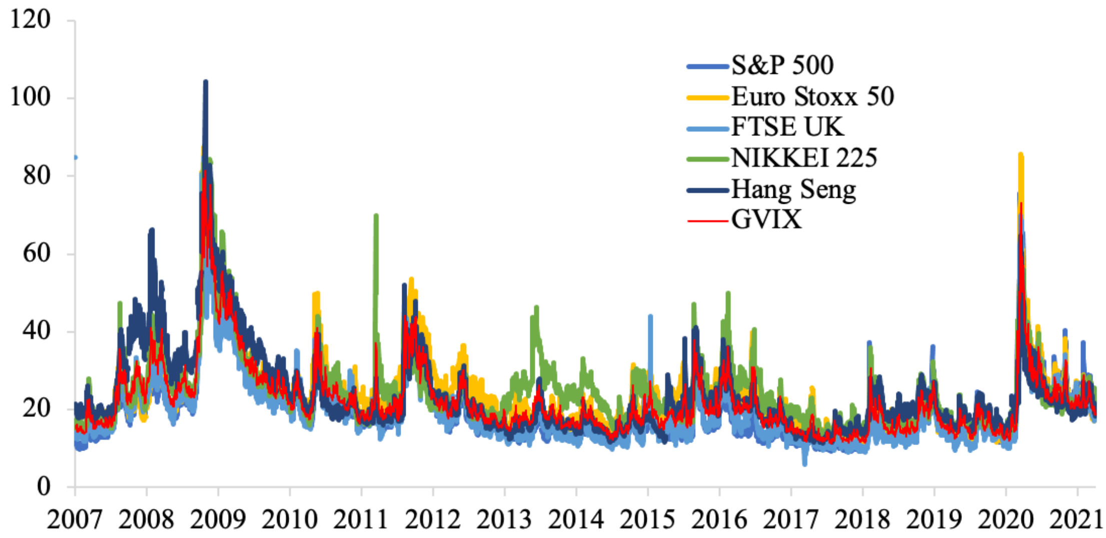
[20] Observations of extreme market scenarios tend to sit at the tails of the statistical distribution. In the parametric model, they are almost by definition considered as outliers that should be removed.

The model is specified as follows:

$$\Delta Basis_{it} = \alpha_i + \beta_i GVIX_t + \beta_{ij}\Delta Control_{jt} + \varepsilon_{it}$$

where $Basis_{it}$ denotes the FX swap or CCBS basis of currency i vis-à-vis the US dollar, $GVIX_t$ represents the state of global financial conditions and $Control_{jt}$ is a list of control variables. $GVIX_t$ is proxied by the first principal component of five major option-implied, hence forward-looking, stock market volatility indices: VIX (for the S&P 500 index), V2X (for the Euro Stoxx 50 index), IVIUK (for the FTSE UK index) VNKY (for the NIKKEI 225 index) and VHSI (for the Hang Seng index) (Figure 7).

Figure 7 Stock Market Volatility Indices



A number of studies regard VIX as an important signal of global banks' leverage cycle that drives banking sector capital flows and global liquidity conditions (Borio and Disyatat, 2011; Gourinchas and Obstfeld, 2012; Obstfeld, 2012a, 2012b; Bruno and Shin, 2014; Rey, 2015). Given that cross-currency markets play an indispensable role in facilitating and financing global banks' cross-border leverage, stock market volatility seems to be a highly relevant proxy for global financial conditions. Since our study covers a wide range of economies across the world, we prefer employing a global proxy instead of just one of these volatility indices, although the results are unlikely to have a material difference whichever one we use.[21]

[21] $GVIX_t$, being the first principal component, explains 90.6% of the total variation of the five indices for the period under study.

There are eight control variables, namely, global dollar strength (the US trade-weighted broad dollar index compiled by the Federal Reserve Board), idiosyncratic dollar strength (the residual obtained by regressing the exchange rate of currency i vis-à-vis the US dollar on the US trade-weighted broad dollar index), exchange rate volatility (the three-month 25-delta FX call option implied volatility of the exchange rate of currency i vis-à-vis the US dollar), exchange rate expectations (the three-month 25-delta FX option risk reversal of the exchange rate of currency i vis-à-vis the US dollar), exchange rate market liquidity (the bid-ask spread of the three-month forward exchange rate of currency i vis-à-vis the US dollar), interest differential (the spread of the ten-year government bond yield of currency i over the ten-year US Treasury bond yield), term spread (the ten-year over two-year spread differential between currency i government bond and US Treasury markets), and credit spread (the spread of US dollar denominated sovereign and corporate bond yields of economy i over US treasury yields). The data for most of these control variables are available for most currencies with only a few exceptions. The potential impact of these variables on dollar funding stress, which is well known and discussed in many previous studies, shall not be repeated here (Avdjiev et al, 2019; Cerutti et al, 2021; Tang and Wong, 2022).

4.2 Estimation results

All data are tested for stationarity. All the three-month bases are found to be stationary except for THB, while most of the five-year bases have a unit root (Appendix D). To ensure stationarity across all currencies to enable consistent comparison, we take first difference of all the three-month and five-year bases for our estimation. $GVIX_t$, which is stationary, is specified in levels.[22] All the control variables are in first difference.

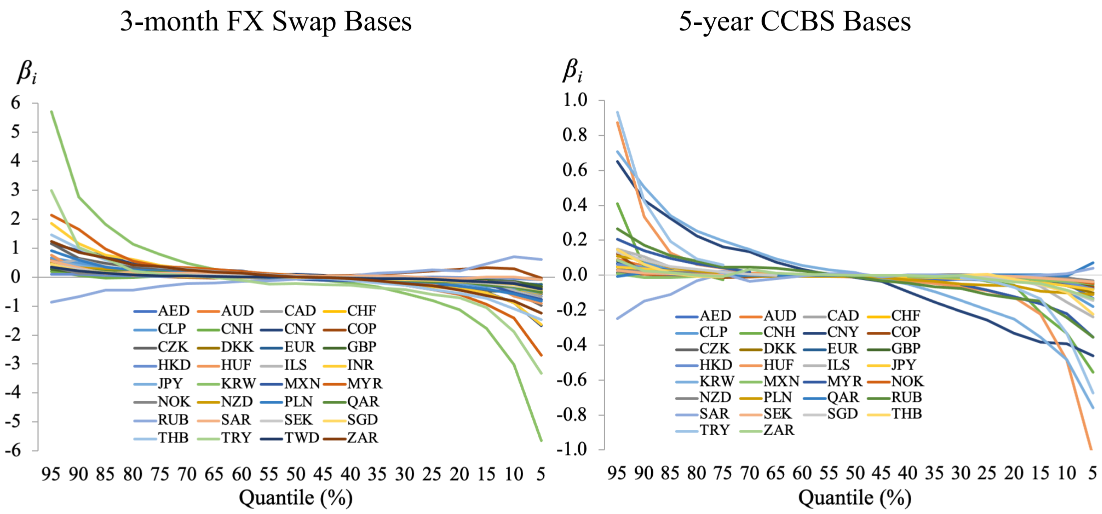
Based on the model specified above, we estimate the relationship between the cross-currency bases and $GVIX_t$ across a wide spectrum of market conditions at every 0.05 quantile from the 95% to the 5% quantile. Given the market practice that the basis is quoted in a way that the more negative (positive) the basis the more stressful (benign) are the dollar funding conditions, the 95% quantile can be taken to represent the most benign or complacent market conditions and the 5% quantile to denote the most adverse or stressful. The median estimate, i.e., the estimate at the 50% quantile, can be interpreted as the one for the normal market.

Figure 8 shows the QR estimates of the responsiveness of the three-month and five-year bases to $GVIX_t$ ranging from the 95% to the 5% quantile. As can be seen, the estimates of the currencies vis-à-vis the US dollar generally form a curve that starts with positive convexity on the left to negative convexity on the right. This suggests that when market conditions are benign the relatively low

[22] The Dickey-Fuller GLS test statistic for $GVIX_t$ for the sample period is -3.71, which is well below the critical value of -2.57 at the 1% level.

financial volatility tends to be associated with a larger reduction in dollar funding stress, but when market conditions are adverse the relatively high financial volatility tends to be accompanied by a sharper rise in dollar funding stress. In the middle of the curve, i.e., when the market is relatively calm, the normal financial volatility is generally met with little change in dollar funding pressure.

Figure 8 Cross-currency Basis Response under Various Market Conditions



The fact that the actions are concentrated at both sides on the market extremity scale is further underscored by Figure 9. Figure 8 does not take into account how significant statistically the estimates are. Figure 9 presents maps of their statistical significance across different currencies and quantiles. Starting from the middle of the maps, the more we move to either end of the market extremity scale, the more estimates are found to have a lower p-value as represented by a darker blue. It looks fairly empty in the middle, especially in the map for the five-year CCBS market. At the median, i.e., the 50% quantile, only one of the 32 estimates turns out to be significant at the 5% level for both the three-month and five-year swaps. This implies that dollar funding stress has little tendency of exacerbating or relaxing under normal market conditions.

Figure 9 Statistical Significance Map of Cross-currency Basis Response

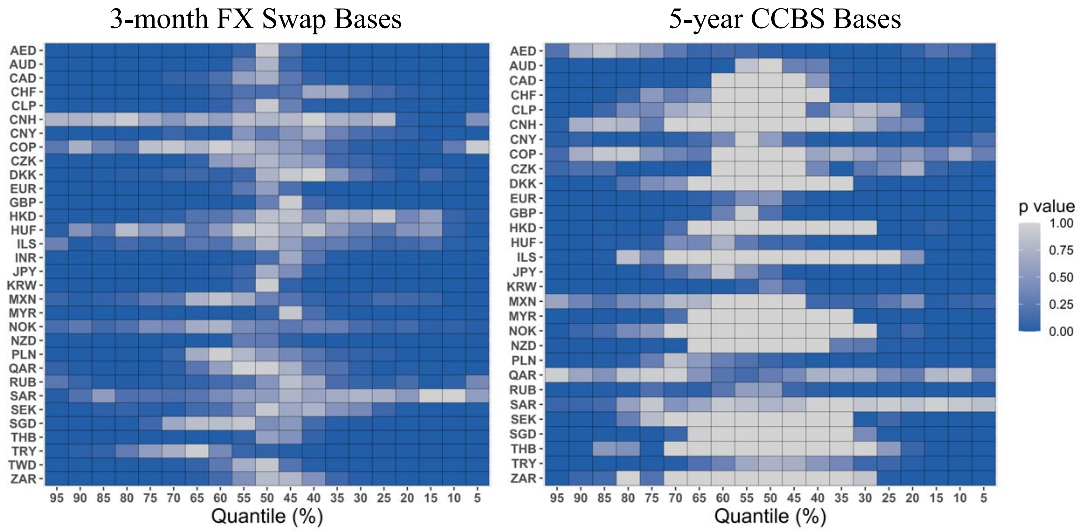


Table 1 puts the spotlight on the normal and the most extreme markets, reporting the OLS estimates and the QR estimates at the 95%, 50% (i.e., median) and 5% quantiles. Both the three-month and five-year bases produce results of very similar flavour. One would be disappointed if one expects to see a negative relationship for the normal market as in most previous studies, as many of the OLS and QR median estimates carry the wrong sign. However, since almost all the estimates, with the exception of the 3-month TRY, are very small in magnitude and statistically insignificant, they can be regarded as practically zero. Overall, the results suggest that during normal market times global financial volatility generally has little impact on dollar funding stress across the board.

On the contrary, at the 95% quantile most of the estimates, 28 out of 32 three-month bases and 25 out of 30 five-year bases, are statistically significant, with a vast majority registering significance at the 1% level. These results are almost the same for the 5% quantile, with 28 out of 32 three-month bases and 26 out of 30 five-year bases being statistically significant. Furthermore, none of the statistically significant estimates carry the wrong sign. This is very strong econometric evidence that global financial volatility tends to be associated with sharp rises in dollar funding stress under the most adverse market conditions, and vice versa in the most complacent market.

For ease of comparison, we rank the currencies according to the intensity of their response under the most extreme market scenarios, i.e., under the 95% and 5% quantiles, in Figure 10. Generally speaking, emerging market currencies tend to be located at the more responsive end of the chart while those of advanced economies at the other end. In terms of magnitude, emerging market currencies are several times more responsive than advanced economy currencies. Hence, in times of crisis, they actually beg much closer monitoring compared to the G3 currencies that usually grab attention in the media and policy forums.

Figure 11 plots the statistically significant estimates at the 95% quantile against those at the 5% quantile for the three-month and five-year bases. The scatterplots show that the dots in general lie fairly close to the 45-degree line. This suggests that the rate at which dollar funding pressure eases for any economy under benign market conditions is almost the same as the rate at which it tightens under stressful market circumstances. More dots fall below the 45-degree line than above, especially for the five-year bases, but not significantly, meaning that cross-currency bases tend to be only marginally more responsive in a stressful market than in a benign market. In all, it is imperative that policymakers not be relaxed when they see signs of significant easing of the stress emerge for some economies, as these economies are also the ones that tend to be hit harder when the tide turns.

Table 1 Cross-currency Basis Response in Normal and Extreme Markets

Currency	3-month FX Swap Bases				5-year CCBS Bases			
	QR (95%)	OLS	QR (50%)	QR (5%)	QR (95%)	OLS	QR (50%)	QR (5%)
AED	0.661***	0.005	-0.001	-0.608***	0.080	-0.021*	-0.004**	-0.132*
AUD	0.605***	0.032	-0.004	-0.553***	0.090***	0.003	0.000	-0.072***
CAD	0.664***	0.002	-0.008	-0.668***	0.063***	-0.003	0.000	-0.051***
CHF	0.449**	0.012	0.030*	-0.555***	0.049***	-0.007*	0.000	-0.054***
CLP	0.659***	0.002	-0.004	-0.544***	0.148***	-0.007	0.000	-0.179***
CNH	0.191	-0.053	-0.024	-0.244	0.409**	-0.056	0.000	-0.556***
CNY	1.157**	-0.116	0.103	-1.680**	0.651*	0.003	-0.012	-0.460
COP	0.526	0.200	0.033	-0.029	0.121	0.003	0.000	-0.068
CZK	1.164***	-0.014	0.014	-0.974***	0.015*	-0.002	0.000	-0.042***
DKK	0.290***	0.004	0.012	-0.347***	0.083***	-0.010**	0.000	-0.102***
EUR	0.313***	0.014	-0.005	-0.258***	0.069***	-0.003	-0.001	-0.078***
GBP	0.267***	0.012	0.006	-0.311***	0.047***	-0.003	-0.002	-0.055***
HKD	0.096*	-0.005	-0.002	-0.097*	0.063***	-0.001	0.000	-0.079***
HUF	0.766**	-0.010	0.024	-0.909***	0.872***	-0.014	-0.010	-1.037***
ILS	0.438	0.004	-0.012	-0.763**	0.149***	-0.016	0.000	-0.239***
INR	1.864***	0.075	0.064	-1.633***	—	—	—	—
JPY	0.542***	0.015	0.009	-0.491***	0.047***	-0.008*	-0.003	-0.082***
KRW	5.719***	-0.104	-0.004	-5.639***	0.708***	-0.016	0.015	-0.760***
MXN	0.524*	-0.044	-0.068	-0.764***	0.010	-0.014	0.000	-0.051*
MYR	2.134***	0.020	0.063	-2.696***	0.206***	-0.025*	0.000	-0.356***
NOK	0.373*	0.021	-0.053	-0.535*	0.030***	-0.006*	0.000	-0.048***
NZD	0.493***	0.000	-0.015	-0.464***	0.031**	0.002	0.000	-0.033***
PLN	0.908***	-0.012	-0.028	-0.833***	0.110***	-0.021	-0.007	-0.109**
QAR	0.335**	0.003	0.001	-0.520***	0.006	0.012	0.000*	0.072
RUB	-0.867	-0.036	-0.061	0.606	0.267***	-0.032	-0.010	-0.355***
SAR	0.548***	0.116*	0.054	-0.087	-0.248	-0.011	0.013	0.039
SEK	0.442***	0.005	-0.004	-0.423***	0.029***	-0.001	0.000	-0.037***
SGD	0.442***	-0.002	-0.017	-0.423***	0.131***	-0.001	0.000	-0.144***
THB	1.463***	-0.062	0.023	-1.475***	0.146***	-0.014	0.000	-0.223***
TRY	2.989**	-0.089	-0.227**	-3.324***	0.932***	0.039	0.000	-0.675***
TWD	0.347***	0.014	-0.001	-0.404***	—	—	—	—
ZAR	1.243***	-0.006	0.014	-1.237`***	0.088***	-0.016	-0.001	-0.134***

Notes: (1) ***, ** and * denote significance at a level of 1%, 5% and 10% respectively. (2) Quantile regression is estimated at quantiles of 0.95, 0.5 and 0.05.

Figure 10 Currency Basis Response Rankings in Extreme Markets

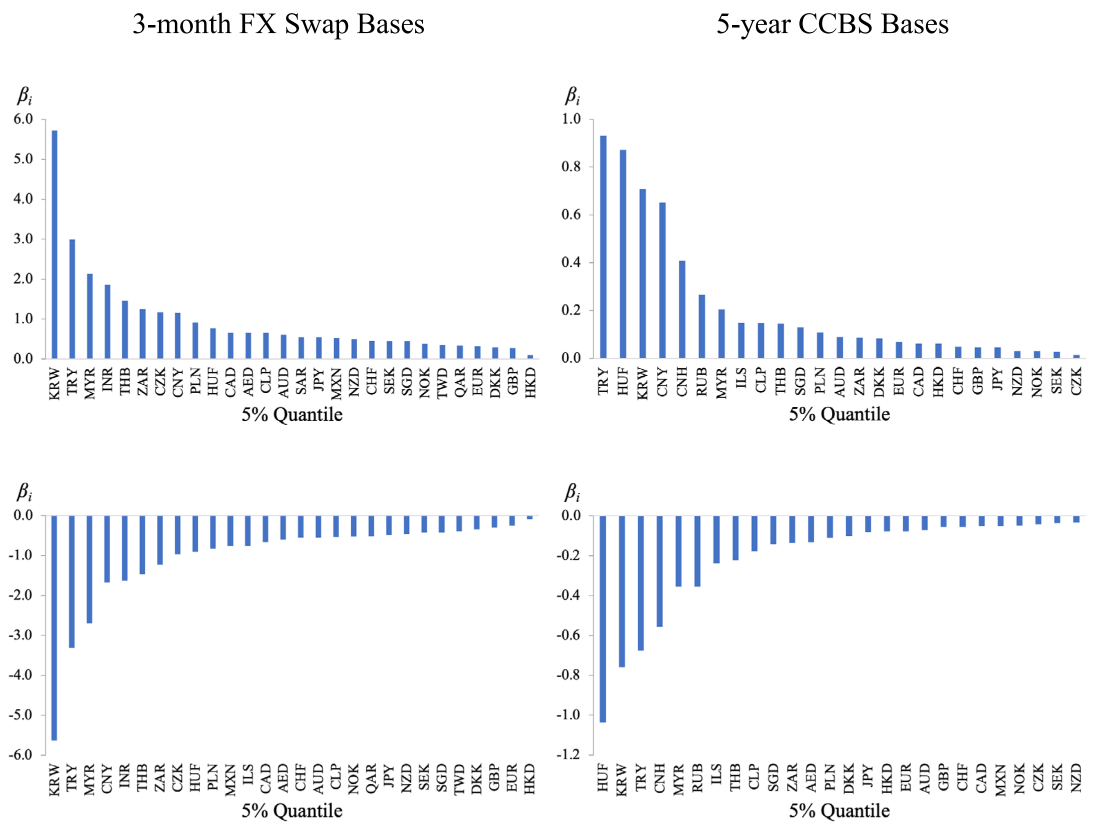
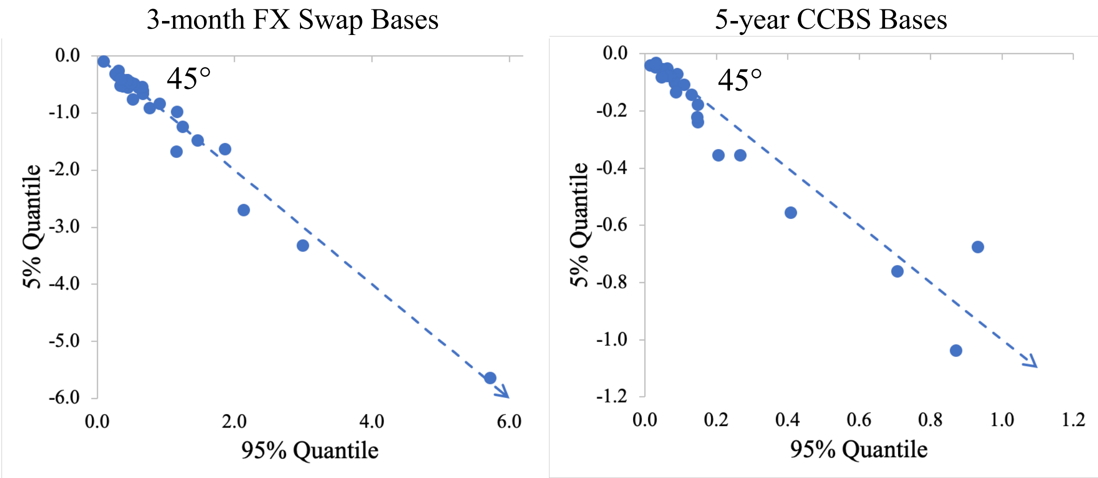


Figure 11 Benignity vs Stressfulness in Cross-currency Swap Markets



5. Conclusion

Since the global financial crisis, non-US financial institutions around the world have continued to experience difficulties in obtaining dollar funding. The resulting stress facing emerging market economies is particularly severe, a fragility that needs to be addressed urgently from the perspective of global financial stability. Different stages of international financial integration, coupled with diversity in economic structure and financial sector development, probably underscore the considerable difference in timing and the extent to which these economies are strained in dollar funding markets. These add to the complexity in any attempt to fathom the difficulties facing them but would be interesting and important aspects to explore. It is hoped that our findings could form a useful foundation for further research in this direction.

In concluding this paper, we would like to highlight three implications of its findings. Firstly, the findings run counter to the notion that dollar funding stress is a global phenomenon. True, it is global in the sense that economies around the world have since the global financial crisis continued to experience such strains to various extent. However, the way it happens is largely unsynchronized. With a few exceptions, cross-currency bases are generally found to be uncorrelated, in particular at the short end of the market. This is especially true with those of emerging market currencies, of which many are in fact negatively correlated with those of advanced economy currencies. Hence, focusing on the G3 or G10 currencies, as is often the case in the media and much of the literature, could potentially be misleading about what happens to the rest of the world.

Second, dollar funding stress in emerging market economies has received far less attention than deserved. While emerging market currencies account for a small share of cross-currency swap trading globally, the past decade or so has seen a significant growth relative to advanced economy currencies. More importantly, this is a group of economies whose dollar funding conditions change more erratically as a whole, move more disproportionately among themselves, and are subject more to the influence of global financial volatility in times of adversity. Given the interconnectedness of the global financial system, the potential contagion must not be underestimated. Hence, to provide an effective liquidity backstop and safeguard global financial stability, the Federal Reserve may consider extending its swap line assistance to cover at least those whose dollar funding conditions are potentially most vulnerable.

Last but not least, it is dangerous to be complacent when we see dollar funding stress recede in good times. When dollar funding strains flash signs of easing, it is often tempting to attribute the favourable development to improvements in the financial conditions of the economy concerned. However, our results show that the economies that experience significant reductions in dollar funding stress in good times are also likely to be the ones that find themselves coming under more severe stress in bad times. This means that for these economies, despite the welcomed signs of development, sudden reversal in dollar funding conditions can occur. Hence, efforts in establishing liquidity backstop facilities and mechanisms are suitable avenues to minimise the impacts on their financial markets.

References

Avdjiev, S, Du, W, Koch, C, and Shin, HS (2019). "The dollar, bank leverage, and deviations from covered interest parity," *American Economic Review: Insights* 1(2): 193-208.

Avdjiev, S, Egemen, E and McGuire, P (2020). "Dollar funding costs during the Covid-19 crisis through the lens of the FX swap market," BIS Bulletin No.1.

Baba, N and Packer, F (2009). "Interpreting deviations from covered interest parity during the financial market turmoil of 2007-08," *Journal of Banking & Finance* 33(11): 1953-1962.

Bank for International Settlements (2020). "US dollar funding: an international perspective," CGFS Papers No.65.

Bellrose, K and Norman D (2019). "The nature of Australian banks' offshore funding," *Reserve Bank of Australia Bulletin* December: 61–70.

Board of Governors of the Federal Reserve System (2021). "Vulnerabilities in US global dollar funding markets," *Financial Stability Report* May: 55-61.

Borio, C, and Disyatat P (2011). "Global imbalances and the financial crisis: link or no link?" BIS Working Papers 346, Bank for International Settlements.

Borio, C, Iqbal, M, McCauley, R, McGuire, P and Sushko, V (2016). "The failure of covered interest parity: FX hedging demand and costly balance sheets," BIS Working Paper No. 590, Bank for International Settlements.

Brunnermeier, MK, Nagel, S and Pedersen LH (2008). "Carry trades and currency crashes," *NBER Macroeconomics Annual* 23 (1): 313–348.

Bruno, V, and Shin HS (2014). "Cross-border banking and global liquidity," BIS Working Papers 458, Bank for International Settlements.

Cerutti, EM, Obstfeld, M and Zhou, H (2021). "Covered interest parity deviations: macrofinancial determinants," *Journal of International Economics* 130: forthcoming.

Diewert, EW (1976). "Exact and superlative index numbers", *Journal of Econometrics* 4(2): 115-145.

Divisia, F (1925/1926). L'indice monétaire et al théorie de la monnaie. *Revue D'Economie Politique* 39(4): 842–864; 39(5), 980–1008; 39(6), 1121–51; 40(1), 49–81.

Eguren-Martin, F (2020). “Dollar shortages and central bank swap lines” Bank of England Staff Working Paper No. 879.

Engle RF and Sheppard K (2001). “Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH,” NBER Working Paper No. w8554.

Fong, TPW, and Wong, AYT (2012). “Gauging potential sovereign risk contagion in Europe,” *Economics Letters* 115: 496–499.

Gourinchas, PO, and Obstfeld, M (2012). “Stories of the twentieth century for the twenty-first,” *American Economic Journal: Macroeconomics* 4(1): 226-265.

Hutchison, M, Pasricha, G and Singh, N (2012). “Effectiveness of Capital Controls in India: Evidence from the Offshore NDF Market,” *IMF Economic Review* 60: 395–438.

International Monetary Fund (2019). “Banks’ dollar funding: A source of financial vulnerability,” Chapter 5 in *Global Financial Stability Report* September: 61-79.

Koenker, R, and Bassett, G (1978). “Regression quantiles,” *Econometrica* 46: 33–50.

Ma, L, and Pohlman, L (2008). “Return forecasts and optimal portfolio construction: A Quantile Regression Approach,” *European Journal of Finance* 14(5): 409–425.

McGuire, P, and von Peter G (2012). “The Dollar Shortage in Global Banking and the International Policy Response,” *International Finance* 15(2): 155–78.

Obstfeld, M (2012a). “Financial flows, financial crises, and global imbalances,” *Journal of International Money and Finance* 31: 469-480.

Obstfeld, M (2012b). “Does the current account still matter?” *American Economic Review* 102(3): 1-23.

Reserve Bank of Australia (2020). “Recent developments in foreign exchange markets,” Box B in *Statement on Monetary Policy* May 2020: 39-43.

Rey, H (2015). “Dilemma not trilemma: The global financial cycle and monetary policy independence,” NBER Working Paper No. 21162.

Siripurapu, A (2020). “The dollar: The world’s currency,” *Foreign Affairs*.

Murtagh, F and Legendre, P (2014). “Ward's hierarchical agglomerative clustering method: which algorithms implement Ward's criterion?” *Journal of Classification* 31: 274–295.

Rousseeuw, PJ (1987). “Silhouettes: A graphical aid to the interpretation and validation of cluster analysis,” *Computational and Applied Mathematics* 20: 53–65.

Tang, Y and Wong, A (2022). “What drives dollar funding stress in distress?” Forthcoming in *International Journal of Central Banking*.

Törnqvist, L (1936). “The Bank of Finland’s consumption price index,” *Bank of Finland Monthly Bulletin* 10: 1–4.

Wong, A and Zhang, J (2018). “Breakdown of covered interest parity: mystery and myth,” BIS Paper No. 96: 57-78.

APPENDIX A SOURCES AND DESCRIPTIVE STATISTICS OF THE DATA

Table A1 Sources and Descriptive Statistics of 3-month FX Swap Bases

Currency	Currency	Min.	Mean	Median	Max.	SD	Sample size	First sample date	Data source
Emirati dirham	AED	-676.6	-67.5	-42.1	225.4	80.3	3713	08 Jan 2007	Bloomberg
Australian dollar	AUD	-130.4	10.8	9.2	241.2	15.0	3717	02 Jan 2007	Bloomberg
Canadian dollar	CAD	-177.2	-18.8	-19.0	150.0	18.1	3717	02 Jan 2007	Bloomberg
Swiss franc	CHF	-250.0	-25.0	-21.7	110.1	24.3	3717	02 Jan 2007	Bloomberg
Chilean peso	CLP	-297.3	-52.6	-39.3	97.7	61.3	2838	17 May 2010	Bloomberg, JP Morgan
Chinese renminbi (offshore)	CNH	-167.3	-37.7	-37.6	327.3	40.5	2028	24 Jun 2013	Bloomberg, CEIC
Chinese renminbi (onshore)	CNY	-2512.0	-180.9	-140.7	1350.0	357.6	3715	04 Jan 2007	Bloomberg, JP Morgan
Colombian peso	COP	-521.7	9.8	10.7	750.4	72.9	2261	01 Aug 2012	Bloomberg
Czech koruna	CZK	-469.9	-68.1	-52.7	434.0	64.4	3717	02 Jan 2007	Bloomberg, Czech National Bank
Danish krone	DKK	-325.3	-55.8	-50.8	54.2	32.6	3717	02 Jan 2007	Bloomberg
Euro	EUR	-264.9	-28.4	-23.7	65.9	25.3	3717	02 Jan 2007	Bloomberg
British pound	GBP	-211.4	-15.4	-10.8	40.2	21.0	3717	02 Jan 2007	Bloomberg
Hong Kong dollar	HKD	-83.4	-17.0	-16.7	57.4	14.5	3717	02 Jan 2007	Bloomberg
Hungarian forint	HUF	-617.5	-57.6	-50.0	138.8	71.3	3717	02 Jan 2007	Bloomberg, Magyar Nemzeti Bank
Israeli New shekel	ILS	-367.8	-35.4	-24.7	822.8	59.7	3717	02 Jan 2007	Bloomberg
Indian rupee	INR	-1238.3	-95.7	-57.6	343.2	144.1	3717	02 Jan 2007	Bloomberg, JP Morgan
Japanese yen	JPY	-256.5	-27.5	-24.1	71.3	21.1	3717	02 Jan 2007	Bloomberg
Korean won	KRW	-1761.3	-97.5	-60.9	1215.7	137.8	3716	02 Jan 2007	Bloomberg
Mexican peso	MXN	-213.0	-25.3	-26.0	865.8	75.3	3715	04 Jan 2007	Bloomberg
Malaysian ringgit	MYR	-753.6	-58.3	-50.4	494.6	73.5	3716	03 Jan 2007	Bloomberg
Norwegian krone	NOK	-791.0	-24.0	-20.9	580.2	35.0	3717	02 Jan 2007	Bloomberg
New Zealand dollar	NZD	-54.4	17.7	14.9	162.5	16.2	3716	03 Jan 2007	Bloomberg, Reserve Bank of New Zealand
Polish zloty	PLN	-295.4	-39.8	-28.3	190.2	43.7	3717	02 Jan 2007	Bloomberg
Qatari riyal	QAR	-172.0	-57.0	-64.4	151.4	43.3	2776	11 Aug 2010	Bloomberg, JP Morgan
Russian ruble	RUB	-789.8	-13.0	-54.4	3656.1	313.0	3712	09 Jan 2007	Bloomberg
Saudi riyal	SAR	-212.7	-46.0	-49.9	181.7	35.9	3713	08 Jan 2007	Bloomberg
Swedish krona	SEK	-263.6	-24.0	-21.3	296.3	25.1	3717	02 Jan 2007	Bloomberg
Singapore dollar	SGD	-271.7	2.8	0.4	301.8	17.7	3716	03 Jan 2007	Bloomberg
Thai baht	THB	-302.2	56.2	-13.8	1266.1	210.7	3716	03 Jan 2007	Bloomberg
Turkish lira	TRY	-540.7	13.2	-22.8	2511.8	200.2	3715	04 Jan 2007	Bloomberg, Banks Association of Turkey
New Taiwan dollar	TWD	-464.4	-84.9	-77.1	94.9	45.0	3717	02 Jan 2007	Bloomberg
South African rand	ZAR	-865.1	46.5	42.5	499.2	49.4	3717	02 Jan 2007	Bloomberg, JPM

Table A2 Sources and Descriptive Statistics of 5-year CCBS Bases

Currency	Currency	Min.	Mean	Median	Max.	SD	Sample size	First sample date	Data source
Emirati dirham	AED	-188.0	-56.3	-47.2	4.5	36.5	3034	14 Aug 2009	Bloomberg
Australian dollar	AUD	-50.0	20.8	22.6	48.0	9.6	3718	01 Jan 2007	Bloomberg
Canadian dollar	CAD	-31.0	0.8	0.8	43.1	10.9	3718	01 Jan 2007	Bloomberg
Swiss franc	CHF	-66.5	-29.1	-28.3	6.0	16.5	3717	02 Jan 2007	Bloomberg
Chilean peso	CLP	-115.6	-29.4	-37.0	41.5	29.6	3482	27 Nov 2007	Bloomberg
Chinese renminbi (offshore)	CNH	-234.0	-99.9	-98.0	15.0	39.9	1798	12 May 2014	Reuters
Chinese renminbi (onshore)	CNY	-501.0	-158.9	-122.0	121.0	114.8	2606	06 Apr 2011	Reuters
Colombian peso	COP	-63.0	-8.5	-12.0	66.7	25.3	1701	24 Sep 2014	Bloomberg
Czech koruna	CZK	-42.6	-15.3	-14.1	10.0	11.9	3718	01 Jan 2007	Bloomberg, JP Morgan
Danish krone	DKK	-85.5	-41.7	-40.5	2.9	19.0	3718	01 Jan 2007	Bloomberg
Euro	EUR	-66.6	-24.0	-22.8	3.0	14.2	3717	02 Jan 2007	Bloomberg
British pound	GBP	-75.0	-7.1	-5.0	16.8	11.8	3717	02 Jan 2007	Bloomberg
Hong Kong dollar	HKD	-63.0	-8.8	-9.0	20.5	12.3	3717	02 Jan 2007	Bloomberg
Hungarian forint	HUF	-151.6	-24.0	-16.0	36.3	29.7	1890	02 Jan 2014	JP Morgan
Israeli New shekel	ILS	-135.0	-52.4	-49.0	-3.0	28.7	3717	02 Jan 2007	Bloomberg
Japanese yen	JPY	-102.5	-48.9	-49.0	34.0	25.2	3718	01 Jan 2007	Bloomberg
Korean won	KRW	-324.0	-92.0	-76.0	5.5	51.6	3717	02 Jan 2007	Bloomberg
Mexican peso	MXN	-156.0	-64.1	-63.5	18.0	34.0	3717	02 Jan 2007	Bloomberg
Malaysian ringgit	MYR	-240.0	-85.6	-79.0	-3.0	41.7	3716	03 Jan 2007	Bloomberg
Norwegian krone	NOK	-43.0	-13.1	-10.5	2.4	9.1	3718	01 Jan 2007	Bloomberg
New Zealand dollar	NZD	-5.5	24.8	26.3	52.0	11.9	3718	01 Jan 2007	Bloomberg
Polish zloty	PLN	-60.0	-13.8	-10.1	43.0	18.4	1890	02 Jan 2014	JP Morgan
Qatari riyal	QAR	-137.1	-85.1	-91.9	39.5	27.8	2110	28 Feb 2013	JP Morgan
Russian ruble	RUB	-333.5	-70.9	-109.5	1000.0	152.9	3707	16 Jan 2007	Bloomberg
Saudi riyal	SAR	-115.5	-35.2	-38.3	102.5	34.2	2959	27 Nov 2009	Bloomberg
Swedish krona	SEK	-28.5	-5.5	-4.8	34.5	7.8	3717	02 Jan 2007	Bloomberg
Singapore dollar	SGD	-69.0	-20.8	-18.7	2.5	12.4	3717	02 Jan 2007	Bloomberg
Thai baht	THB	-205.0	-31.3	-20.0	6.0	34.8	3718	01 Jan 2007	Bloomberg
Turkish lira	TRY	-198.6	-72.9	-86.3	241.9	54.5	1890	02 Jan 2014	JP Morgan
South African rand	ZAR	-103.0	8.4	15.0	55.0	33.2	3718	01 Jan 2007	Bloomberg

APPENDIX B OPTIMIZATION OF FORMING OF CLUSTERS

In the process of clustering, we employ Ward's minimum variance method in which we choose the pair of clusters that leads to a minimum increase in the total within-cluster variance after merging in each step (Murtagh and Legendre, 2014). The increase is a weighted squared distance between cluster centres:

$$\Delta(A,B) = \sum_{i \in A \cup B} \|\vec{x}_i - \vec{m}_{A \cup B}\|^2 - \sum_{i \in A} \|\vec{x}_i - \vec{m}_A\|^2 - \sum_{i \in B} \|\vec{x}_i - \vec{m}_B\|^2$$
$$= \frac{n_A n_B}{n_A + n_B} \|\vec{x}_A - \vec{m}_B\|^2$$

where $\vec{m}_j$ is the centre of cluster j and n_j is the number of points in the cluster. Δ represents the merging cost of combining clusters A and B. With agglomerative hierarchical clustering, the sum of squares starts out at zero (because every point is in its own cluster) and then grows as the clusters merge. Ward's method aims to keep this growth as small as possible.

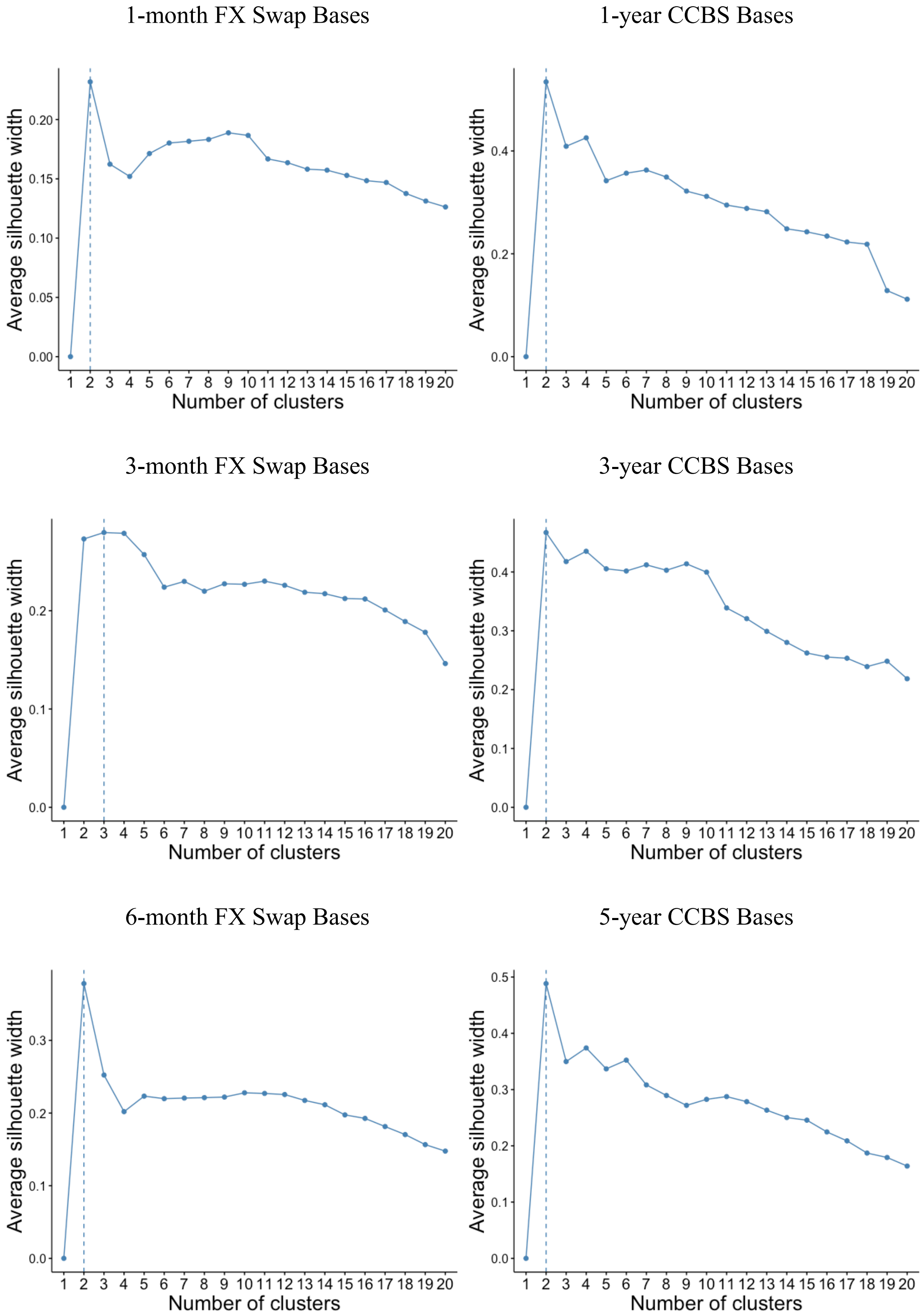
To decide the optimal number of clusters, we use the silhouette method to gauge the quality of the clustering (Rousseeuw, 1987). To do so, the silhouette coefficient is computed to determine how similar an object is to its own cluster relative to other clusters:

$$s(i) = \frac{b(i) - a(i)}{max\{a(i), b(i)\}}, if\ |C_i| > 1\ and\ s(i) = 0, if\ |C_i| = 1$$

where $a(i)$ is the mean distance between i and all the other data points in the same cluster, $b(i)$ is the smallest mean distance of i to all points in any other clusters, and $|C_i|$ represents the number of objects in cluster i. The silhouette coefficient ranges between -1 and 1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighbouring clusters.

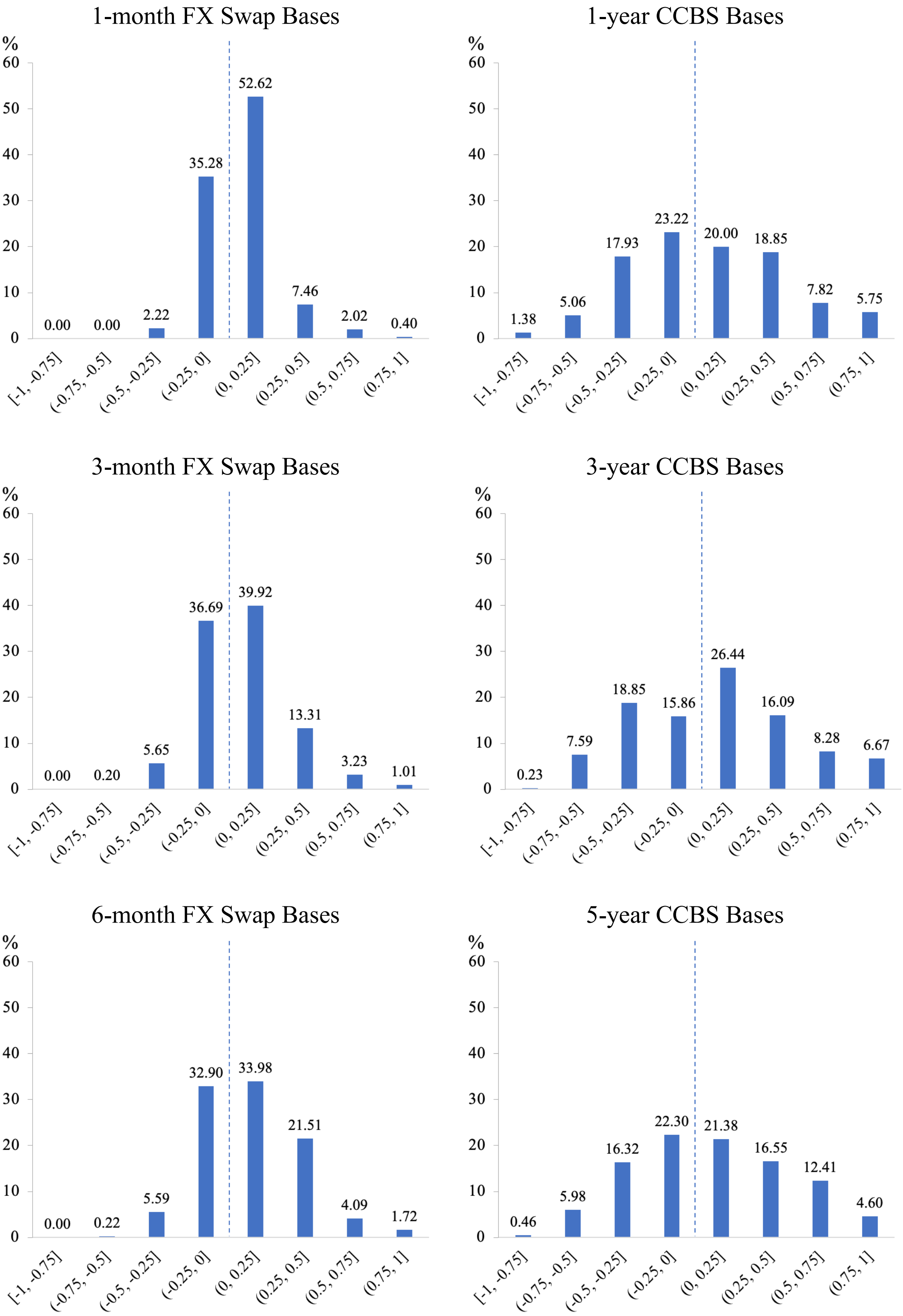
The silhouette coefficients for the correlations between the cross-currency bases across six maturities are plotted in Chart B1. As can be seen, the silhouette coefficient generally continues to climb as the clusters merge until there are only two clusters. The exception is the three-month basis for which the coefficient reaches the highest, but very marginally, when the number of clusters reduces to three.

Figure B1 Silhouette Coefficients of Cross-currency Basis Clustering



APPENDIX C COMPARISON OF CORRELATIONS DISTRIBUTIONS ACROSS MATURITIES

Figure C1 Distributions of Correlations between Cross-currency Bases



APPENDIX D STATIONARITY OF CROSS-CURRENCY BASES

Table D1 Dickey–Fuller GLS Test for Cross-currency Bases

Currency	3-month FX Swap Bases				5-year CCBS Bases			
	Level		First difference		Level		First difference	
AED	-3.04	**	-25.10	**	-1.95	*	-22.27	**
AUD	-7.14	**	-16.94	**	-1.80		-29.43	**
CAD	-6.46	**	-34.18	**	-2.57	*	-17.39	**
CHF	-7.09	**	-21.94	**	-1.08		-23.85	**
CLP	-4.83	**	-20.44	**	-2.98	**	-6.29	**
CNH	-3.06	**	-1.67		-3.29	**	-19.22	**
CNY	-3.58	**	-31.11	**	-0.48		-17.23	**
COP	-2.81	**	-7.25	**	-1.37		-13.63	**
CZK	-4.55	**	-26.69	**	-1.07		-25.55	**
DKK	-3.22	**	-35.20	**	-0.68		-18.52	**
EUR	-4.03	**	-28.59	**	-1.18		-25.25	**
GBP	-5.90	**	-27.91	**	-2.23	*	-23.62	**
HKD	-5.00	**	-7.35	**	-2.11	*	-25.77	**
HUF	-4.22	**	-12.86	**	-0.05		-23.48	**
ILS	-4.23	**	-38.92	**	-0.85		-27.81	**
INR	-3.91	**	-2.03	*	—		—	
JPY	-5.32	**	-18.16	**	-0.59		-24.68	**
KRW	-6.53	**	-18.69	**	-2.37	*	-25.31	**
MXN	-5.19	**	-27.45	**	-1.34		-5.79	**
MYR	-5.21	**	-23.33	**	-1.30		-4.28	**
NOK	-8.56	**	-18.46	**	-1.83		-15.19	**
NZD	-6.22	**	-21.80	**	-1.30		-8.22	**
PLN	-5.43	**	-16.22	**	-0.66		-7.52	**
QAR	-2.25	*	-11.28	**	-2.99	**	-25.94	**
RUB	-5.53	**	-22.20	**	-3.00	**	-14.15	**
SAR	-3.16	**	-27.29	**	-2.79	**	-24.73	**
SEK	-8.56	**	-34.46	**	-2.75	**	-24.02	**
SGD	-6.56	**	-7.31	**	-1.64		-26.03	**
THB	-1.54		-5.46	**	-1.71		-24.44	**
TRY	-7.16	**	-17.64	**	-2.70	**	-14.04	**
TWD	-2.92	**	-5.34	**	—		—	
ZAR	-9.27	**	-8.55	**	-2.32	*	-21.91	**

** and * denote significance at the 1% and 5% level respectively.