



**SENSITIVITY OF EMERGING MARKET BOND FUND FLOWS TO
US MONETARY STANCE AND GLOBAL RISK AVERSION**

Key Points:

- *This note ranks the sensitivities of emerging market economies' (EMEs') bond fund flows to changes in the US monetary stance and global risk aversion. Based on the sensitivities, we draw heat maps to indicate the economies that are more likely to suffer large outflows.*
- *We find that bond fund flows have become more sensitive to changes in the US monetary stance and global risk aversion since the global financial crisis, possibly attributable to an increasing participation of global investors in the EME bond markets through mutual funds.*
- *Some emerging Asian economies, such as Hong Kong, Korea and Singapore, are found to be more resilient in times of market stress and demonstrate lower outflow persistence, which may reflect that global investors are able to differentiate among emerging economies based on their fundamentals.*
- *Our results also show that persistence is relatively high for bond fund inflows to emerging Asian economies, suggesting that policymakers should be vigilant about the risk of large inflows.*

*Prepared by : David Leung, Jiayue Zhang and Alfred Wong
Market Research Division, Research Department
Hong Kong Monetary Authority*

The views and analysis expressed in this paper are those of the authors, and do not necessarily represent the views of the Hong Kong Monetary Authority.

I. INTRODUCTION

The bond markets of emerging market economies (EMEs) have drawn enormous interest from global investors since the Global Financial Crisis (GFC) despite occasional episodes of large withdrawals (e.g., the tapering tantrum in 2013, the US presidential election in 2016). Global investors have increasingly diversified their investment to EME bond markets, as evidenced by the substantial increase in monthly net inflows into EME bond mutual funds during the post-crisis period compared to the pre-crisis period. The cumulated flows to EME bond funds, although dropping to US\$ 5.9 billion after the GFC, rose sharply to US\$220.5 billion by the end of the third quarter of 2017.¹ Within these EME bond funds, larger shares of their portfolios are allocated to government bonds than corporate bonds. According to Morningstar, as of end-September 2017, EME bond funds allocate approximately 54% of their positions to government bonds and 23% to corporate bonds.² A key attraction of EME bonds to global investors is attributable to their relatively high yields in a low-interest-rate environment created by major central banks' unconventional monetary policies. Sound fundamentals of some emerging Asian economies have also been a major pull factor.³

While the increasing participation of global investors has propelled the growth in EME bond markets, it has also made these markets more susceptible to global shocks. Reflecting the effects of these common global factors, bond fund flows to EMEs have shown signs of synchronisation despite the huge disparities in the fundamentals of individual economies.⁴ Hence, there is no surprise that many empirical studies find that global or “push” factors, especially US monetary stance and global risk aversion, have become the key drivers of portfolio flows to EMEs. In comparison, the findings in the existing literature about the role of domestic or

¹ Cumulated flows are calculated as the sum of monthly net flows starting from June 2003, subject to data availability.

² Government bonds refer to (i) conventional debt issued by Central Bank, Treasury and local governments; (ii) debt obligations issued by government agencies as well as interest-rate swaps and Treasury futures whose risk profile commensurate with government bonds; and (iii) municipal bonds. The fund allocation other than government or corporate bonds includes cash & equivalents and various types of derivatives (e.g. swap contracts, futures/ forward contracts).

³ Mishra et al. (2014) find that EMEs with sound fundamentals (e.g. larger current account surplus, stronger fiscal balance, lower inflation and more foreign reserves), such as many emerging Asian economies, were more resilient to shocks, making these markets more attractive to global investors.

⁴ As an indicator of the co-movements of EME bond fund flows, a principal component analysis finds that the first principal component accounts for 91% of the variability of bond fund flows to EMEs for the post-crisis period from July 2009 to December 2016.

“pull” factors have appeared to be less conclusive.⁵ Against this background, we focus on the sensitivity ranking of various EMEs and developed economies towards the push factors.

II. METHODOLOGY

To assess the sensitivity of bond fund flows towards changes in the US monetary stance and global risk aversion, an OLS model and a quantile regression model are estimated.⁶ The coefficients in the OLS model are estimated using Newey-West standard errors to tackle the serial correlation and heteroscedasticity problems. Unlike OLS estimations which evaluate the mean relationship among variables, quantile estimations at extremely high or low quantiles can provide useful information regarding the relationship between dependent and independent variables under economic distress or during market turbulence (Wong & Fong, 2011). In other words, quantile regressions can depict the relationship between bond fund flows and global shocks under extreme market conditions, which is useful for assessing worst-case scenarios for regulators from a financial stability standpoint.

In both OLS and quantile regression models, the dependent variable is the monthly net bond fund flow to an individual economy specified as a percentage of prevailing fund allocation. This specification enhances comparability across economies by rescaling the fund flows. The explanatory variables of interest are US monetary stance and global risk aversion. In addition, the lagged fund flows are included in the model to take into the fact that fund flows appear to be highly persistent. Besides the explanatory variables, we also include the following control variables in the models: global manufacturing conditions, commodity prices, the strength of the US dollar and global emerging market bonds performance. The selected control variables indicate the performance of the real economy and the EME bond markets, which also drive bond fund flows to a certain extent. The model specification is as follows,

⁵ The findings of Audigé (2014), Brana and Lahet (2010), Forbes and Warnock (2012), Fratzscher (2012), Ghosh et al. (2016), Koepke (2015), Milesi-Ferretti and Tille (2011) and Rey (2015) suggest that global factors are crucial in driving portfolio flows. Regarding domestic or pull factors, Brana and Lahet (2010) and Forbes and Warnock (2012) find domestic macroeconomic factors less important in explaining capital flow episodes. However, Fratzscher (2012) and Förster et al. (2014) find that country specific factors have become more dominant after crisis.

⁶ Quantile regression, a non-parametric modelling technique first introduced by Koenker and Bassett (1978), is used extensively in empirical research to uncover extreme relationships.

$$Flow_t = c + \boldsymbol{\beta}' \mathbf{X}_t + \boldsymbol{\gamma}' \mathbf{Z}_t + e_t$$

where $Flow$ represents the net bond fund flow as a percentage of total bond fund allocation to the bond market of an individual economy. The fund flow is regressed on a vector of explanatory variables \mathbf{X} and a vector of control variables \mathbf{Z} , with e being the residual. The constant c and vectors $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the coefficients to be estimated, which represent the sensitivities towards the corresponding factors. The variables \mathbf{X} and \mathbf{Z} are specified as

$$\mathbf{X}_t = \begin{pmatrix} d(FFR_t) \\ d(VIX_t) \\ Flow_{t-1} \\ Flow_{t-2} \\ \dots \\ Flow_{t-l} \end{pmatrix}, \text{ and } \mathbf{Z}_t = \begin{pmatrix} d\log(DXY_t) \\ d(PMI_t) \\ d\log(CRY_t) \\ d\log(EMBI_t) \end{pmatrix}$$

In the explanatory variable \mathbf{X} , FFR is the effective federal funds rate and VIX is the volatility index of the S&P 500. These factors are specified as first differences due to the presence of unit roots. Lagged fund flows ($Flow_{t-1}$, $Flow_{t-2}$, ..., $Flow_{t-l}$) are also included to take autocorrelation into consideration, where the number of lags, l , is determined by the Akaike information criterion (AIC). The rankings of the coefficients in the vector $\boldsymbol{\beta}$ are expected to inform us of the relative sensitivity of fund flows towards the US monetary stance and global risk aversion. In the control variable \mathbf{Z} , DXY represents the strength of US dollar, PMI indicates the global economic health, CRY is a price index of major commodities, and $EMBI$ represents the emerging market bond market performance. All control variables except PMI are specified in log-differences to represent monthly returns.

III. DATA

This study uses a fund flow database compiled by the EPFR Global which provides fund flow and asset allocation data of mutual funds domiciled globally with US\$24 trillion in total assets. The EPFR country flow data consist of aggregated individual fund flows to the bond market of a specific economy based on asset allocation and return information obtained directly from fund managers, which offers a nice balance between data quality and timeliness. US monetary stance is proxied by the effective federal funds rate obtained from the Federal

Reserve and global risk aversion by the S&P 500 VIX index obtained from Bloomberg.⁷ Control variables are proxied by the US Dollar Index return, change in the JPMorgan Global Manufacturing PMI, Thomson Reuters/CoreCommodity CRB Commodity Index return, and total return of the JPMorgan Emerging Market Bond Index. The summary statistics of the dependent and independent variables are presented in Tables 1a & 1b. The number of lags l is determined to be three, according to the AIC of most regressions.

Table 1a: Summary statistics of explanatory variables

Variable	d(FFR)	d(VIX)	dlog(DXY)	d(PMI)	dlog(CRY)	dlog(EMBI)
Name	Change in effective federal funds rate	Change in S&P500 Index volatility	Return of US Dollar Index	Change in JPMorgan Global Manufacturing PMI	Return of Thomson Reuters/Core-Commodity CRB Commodity Index	Total return of JPMorgan Emerging Market Bond Index
Source	Atlanta Fed & St. Louis Fed	Bloomberg	Bloomberg	JPMorgan Markets	Bloomberg	JPMorgan Markets
Unit	(%)	(%)	(%)		(%)	(%)
Mean	0.00	-0.06	-0.01	0.04	-0.07	0.63
Median	0.00	-0.33	-0.10	0.04	0.78	0.74
Max.	0.53	30.94	6.05	4.20	8.50	4.87
Min.	-1.81	-10.23	-4.57	-4.29	-22.72	-2.97
Std. Dev.	0.27	4.00	1.92	1.06	4.37	1.13

Note: The sample period is from June 2003 to September 2017, with the number of observations for each variable being 172.

Source: Atlanta Fed, St. Louis Fed, Bloomberg and JPMorgan.

⁷ As the federal funds target rate was reduced to 0 to 1/4% from 16 December 2008 to 15 December 2015, the Wu-Xia Shadow Federal Funds Rate, which is not subject to the zero-lower-bound problem, is used for this period (Wu & Xia, 2016). For details, see https://www.frbatlanta.org/cqer/research/shadow_rate.aspx?panel=1.

Table 1b: Summary statistics of dependent variable – bond fund flow to each economy as a percentage of allocation (whole period)

(%)	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.	Earliest obs.
Brazil	0.61	0.83	6.72	-10.78	2.24	167	Dec 2003
Bulgaria	0.33	0.50	4.24	-12.32	2.15	157	May 2004
Chile	0.72	1.07	6.20	-10.81	2.13	162	May 2004
China	0.91	0.84	10.52	-10.26	2.63	165	Feb 2004
Colombia	0.87	0.93	6.83	-10.98	2.22	162	May 2004
Croatia	0.46	0.61	7.85	-14.59	2.55	162	May 2004
Egypt	0.86	1.12	6.93	-10.99	2.24	162	May 2004
France	0.36	0.41	5.04	-7.42	1.72	146	Sep 2005
Germany	0.38	0.42	4.28	-6.12	1.46	146	Sep 2005
Ghana	0.73	0.96	6.93	-10.99	2.30	144	Nov 2005
Hong Kong	1.06	0.96	11.25	-10.51	2.48	165	Feb 2004
Hungary	0.34	0.42	10.33	-13.31	2.75	162	May 2004
India	0.86	0.99	10.52	-10.79	2.71	163	Apr 2004
Indonesia	0.86	1.00	10.52	-9.65	2.26	165	Feb 2004
Japan	0.57	0.52	4.52	-5.61	1.31	146	Sep 2005
Kazakhstan	0.83	1.16	6.63	-10.99	2.22	162	May 2004
Korea	0.89	0.81	10.52	-7.90	2.13	165	Feb 2004
Lebanon	0.75	1.03	6.93	-10.99	2.43	150	May 2004
Malaysia	0.90	0.91	10.52	-8.36	2.21	165	Feb 2004
Mexico	0.70	1.03	6.13	-9.82	2.02	163	Apr 2004
Nigeria	0.79	1.12	6.93	-10.99	2.27	162	May 2004
Pakistan	0.89	1.17	7.89	-10.96	2.40	162	May 2004
Panama	0.75	1.13	6.79	-10.95	2.28	162	May 2004
Peru	0.78	1.10	6.28	-10.10	2.15	162	May 2004
Philippines	0.91	0.99	10.52	-10.85	2.40	165	Feb 2004
Poland	0.57	0.59	9.15	-9.68	2.29	162	May 2004
Qatar	0.77	0.93	5.98	-10.99	2.08	162	May 2004
Romania	-0.01	0.18	6.11	-14.59	2.57	162	May 2004
Russia	0.77	1.04	6.28	-10.21	2.11	167	Dec 2003
Singapore	1.02	0.81	11.08	-10.48	2.53	165	Feb 2004
South Africa	0.60	0.89	6.36	-10.85	2.13	167	Dec 2003
Thailand	0.98	0.85	10.52	-10.84	2.50	165	Feb 2004
Tunisia	0.80	1.21	6.93	-10.99	2.36	162	May 2004
Turkey	0.72	1.10	6.33	-11.43	2.34	162	May 2004
Ukraine	0.60	0.84	6.44	-10.44	2.32	115	May 2004
UAE	0.22	0.30	6.28	-5.55	1.43	156	Apr 2008
UK	0.36	0.36	2.53	-3.35	0.78	173	Nov 2004
USA	0.80	1.02	6.66	-11.13	2.19	162	Jun 2003
Venezuela	0.79	1.11	6.19	-10.98	2.20	162	May 2004
Vietnam	0.90	1.14	10.52	-10.97	2.32	165	Feb 2004

Source: EPFR Global

The sample period is from June 2003 to September 2017 subject to data availability for individual economies, and monthly data are used in the empirical analysis. We further divide the sample into three periods, namely the pre-crisis period (June 2003 to July 2007), crisis period (August 2007 to June 2009), and post-crisis period (July 2009 to September 2017) to compare different behaviours under different market conditions.⁸ The sample, subject to data availability, includes 35 EMEs and 5 developed market economies selected based on the classification by the IMF in its *World Economic Outlook*. We group eight of the Asian EMEAP members as emerging Asian economies with the aim to see if these economies are more resilient to shocks in US monetary policy and global risk aversion than other EMEs.⁹

IV. EMPIRICAL RESULTS

a. *Bond fund flows to most economies have become sensitive to the US monetary stance and global risk aversion after GFC.*

Comparing the pre-crisis and post-crisis periods, it is found that bond fund flows have become increasingly sensitive to changes of US monetary stance and global risk aversion. Prior to the GFC, very few of the coefficients β_1 and β_2 are statistically significant for any of the economies in our sample, according to the estimation results of the OLS model (Table 2). However, in the post-crisis period, the number of economies with significant coefficients, β_1 and β_2 , increases to 30 and 39 respectively. The quantile regression results in Table 2 also show that, at various quantiles, more economies have *FFR* and *VIX* coefficients significantly different from zero in the post-crisis period than in the pre-crisis period.

⁸ The sample uses the earliest available data for every economy, the earliest record of each economy can be found in Table 1b. Crisis period is not included in the estimation below, as the time series is too short to generate a meaningful estimation. The crisis period starts in August 2007 because on 8 August 2007, BNP Paribas suspended redemptions for three of its investment funds, a landmark event widely regarded as the starting point of the ensuing turmoil in global financial markets (e.g., Hui et al. (2011), Taylor & Williams (2009)). The crisis period ends in June 2009 according to the National Bureau of Economic Research's business cycle reference dates. Within the post-crisis sample, we further estimated the sensitivities during the taper tantrum (June to December 2013). The sensitivities to US monetary stance rose (higher in significance and larger in magnitude) whereas the sensitivities to global risk aversion remained broadly the same. The results suggest that the higher sensitivity to US monetary stance during the tapering tantrum is a transitory phenomenon and should not affect the whole picture after the GFC.

⁹ EMEAP stands for the Executive Meeting of Emerging Asian Pacific, a cooperative organization of the central banks and monetary authorities (hereinafter "central banks") in the East Asia and Pacific region. In this note, the emerging Asian economies refer to the eight economies whose central banks are members of EMEAP, namely China, Hong Kong, Indonesia, Korea, Malaysia, the Philippines, Singapore and Thailand.

Table 2: Number of economies with fund flows sensitive to US monetary stance, global risk aversion and lagged flow (10% or higher significance level)

Percentile	FFR		VIX		Lagged Flow	
	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
10%	0	2	0	29	1	5
20%	1	3	1	22	17	28
30%	1	5	2	33	21	37
40%	0	1	2	32	22	38
50%	0	3	1	34	24	39
60%	0	3	1	36	18	39
70%	2	7	1	37	13	39
80%	2	13	1	37	13	36
90%	2	16	1	35	1	34
OLS	2	30	1	39	15	40

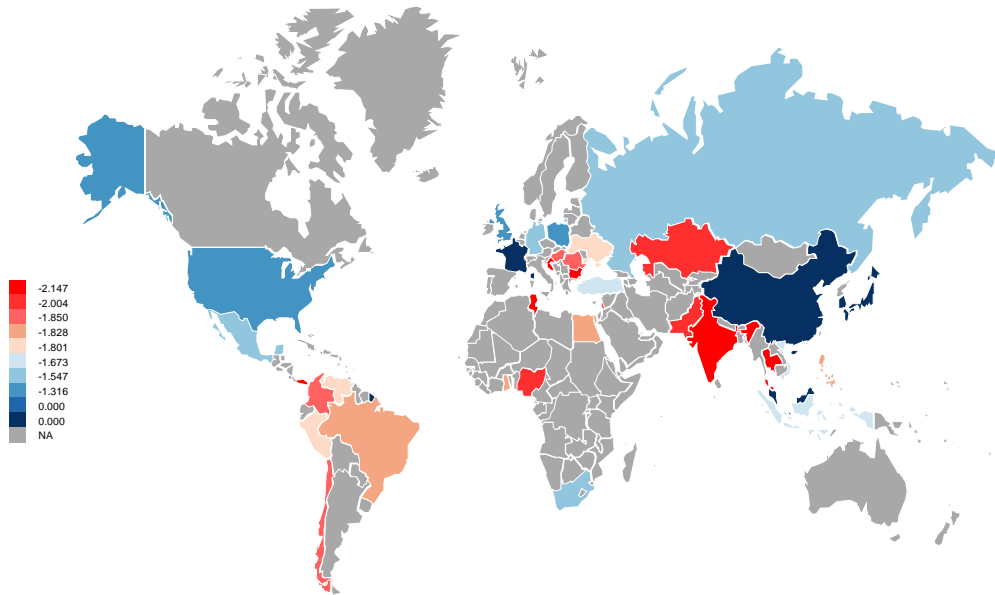
Note: 1. The first nine rows show the number of significant coefficients from regressions estimated at different percentiles (from 10% to 90%).
 2. The last row shows the results for the OLS estimation.

b. *EMEs are more sensitive to the US monetary stance and global risk aversion than developed economies, with emerging Asian economies ranking in between.*

In order to show the differences among the economies, Charts 1a, 1b & 1c plot the maps of post-crisis sensitivity towards the US monetary stance, global risk aversion and one-month lagged flows, estimated from the OLS model. The economies in blue are less sensitive to the respective factor compared with those in red. To be more specific, Table 3 lists 10 economies with the highest and lowest sensitivities during pre- and post-crisis periods.¹⁰ Note that the coefficients for US monetary stance and global risk aversion in the post-crisis period are negative for most of the economies, indicating that a US rate hike or an increase in global risk aversion would *ceteris paribus* trigger bond fund outflows. From the charts and the table, two observations are worth noting.

¹⁰ For each coefficient ranking, economies are divided into two groups by the threshold of 10% significance level. The economies in each group are ranked by the absolute value of coefficients separately, i.e. the higher the absolute value the higher the sensitivity rank. Then the significant group ranks higher than the insignificant group.

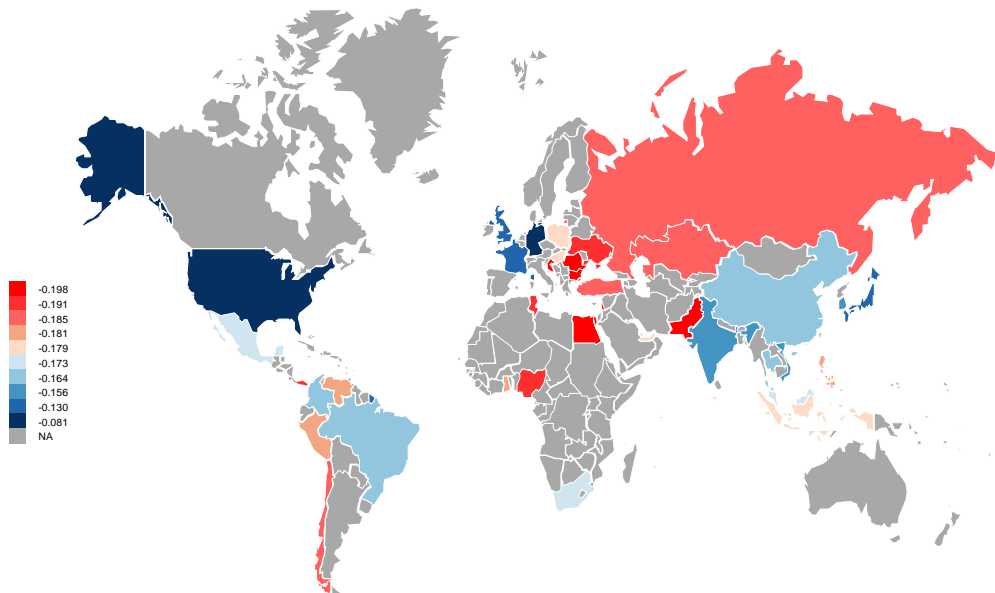
Chart 1a: Sensitivity to FFR in post-crisis period (OLS)



Note: Colour scale is according to percentile of coefficients. The coefficients insignificant at 10% or higher level are treated as zero.

Source: *CIA World Fact Book and authors' estimates.*

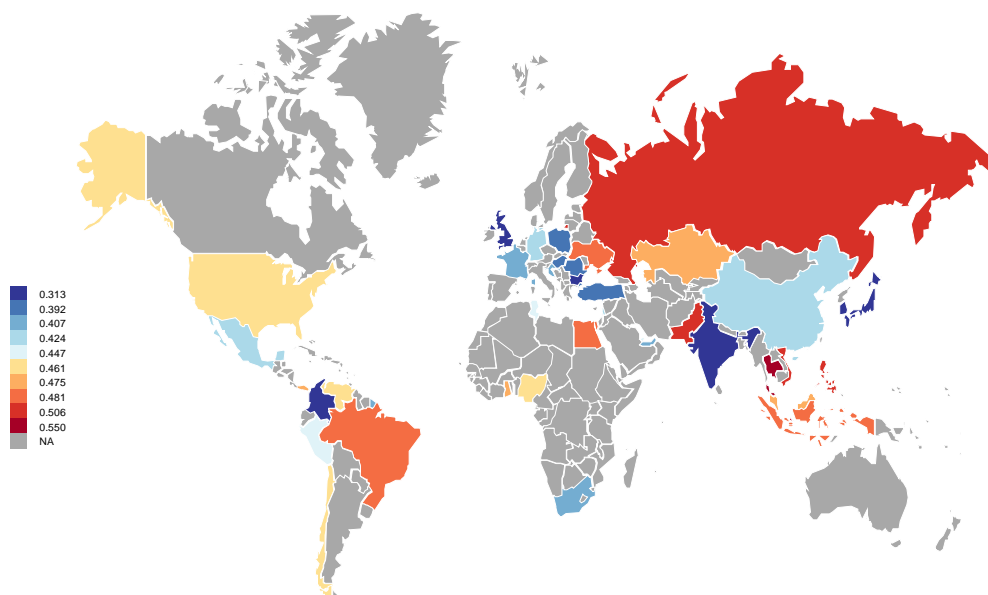
Chart 1b: Sensitivity to VIX in post-crisis period (OLS)



Note: Colour scale is according to percentile of coefficients. The coefficients insignificant at 10% or higher level are treated as zero.

Source: *CIA World Fact Book and authors' estimates.*

Chart 1c: Sensitivity to one-month lagged flow in post-crisis period (OLS)



Note: Colour scale is according to percentile of coefficients. The coefficients insignificant at 10% or higher level are treated as zero.

Source: *CIA World Fact Book and authors' estimates.*

First, compared to developed markets, EMEs face heavier outflow pressures in case of a tightening of US monetary policy or an increase in global risk aversion, other things being equal. In particular, in the post-crisis period, economies that are most sensitive to the US monetary stance and global risk aversion are all EMEs, whereas all the developed economies rank among the least sensitive ones (Charts 1a & 1b). The higher sensitivity of EMEs is possibly attributable to the fact that flows into EMEs' bond markets are driven by search-for-yield activities, which would reverse when yields in the developed markets rise again. Also, EME bonds are typically perceived to be riskier than bonds of developed markets, which are likely to face more selling pressures during risk-off periods.

Second, some economies in emerging Asia, such as Hong Kong, Singapore and Korea, rank among the least sensitive (Table 3). This may be attributable to the fact that these economies have relatively sound economic fundamentals and/or more sophisticated financial market frameworks.¹¹ Their lower sensitivity to the US monetary stance and global risk aversion suggests that global investors are now more able to distinguish among EMEs, rather than regarding all EME bonds as a single asset class and buying/selling them across the board. These findings are also consistent with earlier studies that economies with stronger fundamentals, deeper financial markets and a tighter macroprudential policy stance experienced smaller increases in their government bond yields in response to the 2013 tapering tantrum (Mishra et al., 2014). Another possible factor for the resilience of emerging Asian bond markets is the predominant use of fixed-rate bonds by corporates since the GFC, as a recent research by S&P Global (2016) indicates that regions with higher portion of floating-rate debt are more vulnerable to interest rate shocks. Dealogic data show that floating-rate corporate debt accounted for only 11.5% of the newly issued corporate debt by emerging Asian issuers during 2003-2007, with 4.8% indexed to US dollar Libors. The figures decreased sharply to 2.1% and 0.9% respectively during 2011-2015.

¹¹ IMF (2017) concludes that while the external environmental including the US rate hikes are challenging, Hong Kong's "strong policy frameworks ... are in place to weather a less favourable environment." Balakrishnan et al. (2013) find that net capital inflows to Hong Kong and Korea have surged following the GFC, likely reflecting the "status as a financial center". Besides, active policy support also encourages bond market development in emerging Asia. For example, the Asian Bond Fund Initiative 2 established by EMEAP central banks designates private sector fund managers to invest in local currency denominated bonds in EMEAP Asian economies, and the Asian Bond Market Initiative launched by the ASEAN+3 framework also encourages local bond market development. These efforts have led to significant improvements in the local bond markets (Chan et al., 2012).

Table 3: Sensitivity rankings of bond fund flows during pre- and post-crisis periods (OLS)

Category	Rank	FFR				VIX				Flow(-1)			
		Pre-crisis		Post-crisis		Pre-crisis		Post-crisis		Pre-crisis		Post-crisis	
Most sensitive	1	Romania	3.88 *	Bulgaria	- 3.15 ***	France	- 0.26 *	Egypt	- 0.20 ***	Romania	0.77 ***	Singapore	0.62 ***
	2	Croatia	3.69 *	India	- 2.70 ***	UAE	- 0.18 ***	Bulgaria	- 0.20 ***	Japan	0.74 ***	Thailand	0.55 ***
	3	Russia	2.19 **	Thailand	- 2.09 **	India	- 0.21	Croatia	- 0.20 ***	Hungary	0.72 ***	Philippines	0.55 ***
	4	Bulgaria	2.01 *	Croatia	- 2.05 ***	Russia	- 0.18	Romania	- 0.19 ***	Poland	0.68 ***	Pakistan	0.52 ***
	5	Brazil	1.98 *	Panama	- 2.03 **	Japan	- 0.15	Lebanon	- 0.19 ***	Croatia	0.67 ***	Vietnam	0.51 ***
	6	UAE	- 1.93 ***	Tunisia	- 2.02 **	Qatar	- 0.15	Pakistan	- 0.19 ***	India	0.64 ***	Russia	0.51 ***
	7	South Africa	1.30 *	Lebanon	- 2.00 **	South Africa	- 0.13	Tunisia	- 0.19 ***	Singapore	0.59 **	Egypt	0.51 ***
	8	Hungary	4.31	UAE	- 1.93 ***	Bulgaria	- 0.13	Panama	- 0.19 ***	Russia	0.56 ***	Brazil	0.49 ***
	9	Poland	3.41	Kazakhstan	- 1.91 **	Germany	- 0.13	Nigeria	- 0.19 ***	France	0.54 **	Indonesia	0.49 ***
	10	Ghana	3.33	Nigeria	- 1.89 **	Chile	- 0.12	Ukraine	- 0.19 ***	Korea	0.54 **	Ukraine	0.48 ***
Least sensitive	1	Malaysia	0.04	Japan	0.30	Thailand	- 0.00	Germany	- 0.04	USA	0.15	India	0.24 **
	2	Thailand	- 0.26	France	- 0.47	Croatia	0.00	USA	- 0.05 ***	Vietnam	0.18	UK	0.27 **
	3	Indonesia	0.33	Korea	- 0.71	Malaysia	0.00	UK	- 0.08 ***	Brazil	0.22	Bulgaria	0.32 ***
	4	Korea	- 0.37	Singapore	- 1.18	Korea	0.01	Japan	- 0.10 ***	Philippines	0.24	Japan	0.33 **
	5	USA	- 0.61	Hong Kong	- 1.37	Indonesia	0.01	Hong Kong	- 0.11 ***	China	0.25	Colombia	0.37 ***
	6	Japan	0.69	Malaysia	- 1.38	Singapore	- 0.01	France	- 0.13 ***	UK	0.27	Korea	0.38 ***
	7	UK	- 0.69	China	- 1.67	China	- 0.02	India	- 0.13 **	Lebanon	0.30	Hungary	0.39 ***
	8	China	0.76	UK	- 0.57 *	Poland	0.02	Singapore	- 0.14 ***	Panama	0.33	Poland	0.40 ***
	9	Singapore	- 0.83	USA	- 1.06 **	Romania	- 0.02	Korea	- 0.15 ***	Ghana	0.33	Romania	0.40 ***
	10	Hong Kong	- 0.84	Poland	- 1.27 **	UK	- 0.03	Vietnam	- 0.15 ***	Peru	0.34	Turkey	0.41 ***

- Note: 1. The economies in each column are ranked by the absolute value of their coefficients provided that they are significant at the 10% or higher significance level. Those not significant at the 10% are also ranked by the absolute value of coefficients, but meaningful interpretation of the ranking is limited.
2. *, **, and *** represent the significance levels of 10%, 5% and 1%.
3. Names of developed economies are highlighted in blue and emerging Asian economies in red.

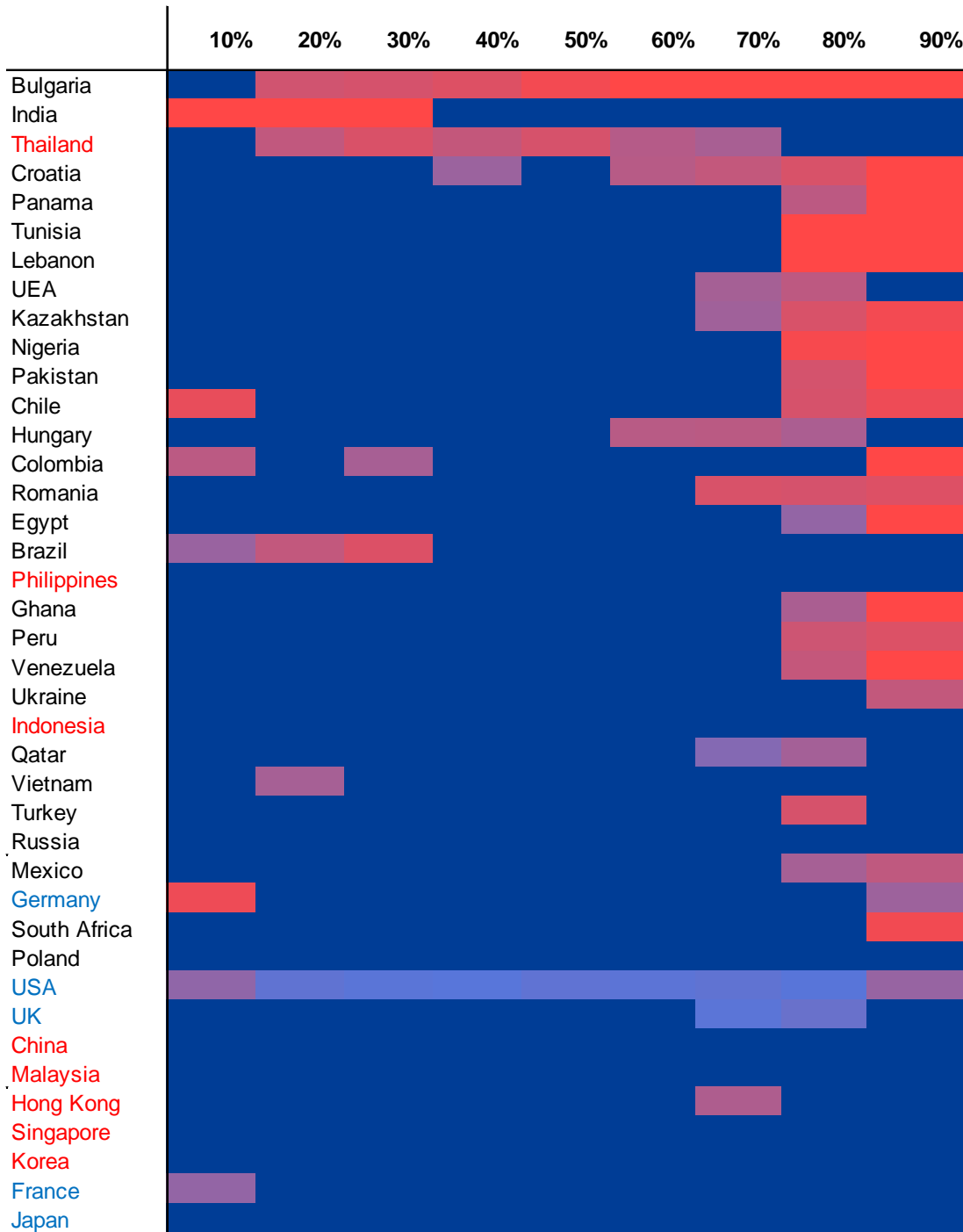
- c. *In extreme scenarios, EMEs are more resilient to shocks in the US monetary stance and global risk aversion but face higher risks of destabilising inflows during good times.*

In order to better visualise the sensitivity of fund flows to changes in the US monetary stance and global risk aversion under different scenarios for each economy, we draw a heat map for each variable of interest according to individual economies' sensitivities at various quantiles, where the colour of cells corresponds to the relative magnitude of the coefficients in quantile regressions. In Chart 2, red indicates high risk of outflows during rate-hike periods, and blue and navy blue respectively indicate that bond fund flows are less sensitive (significant but small in magnitude) and insensitive (insignificant) to changes in US monetary stance. As can be seen from the dominance of navy blue cells, emerging Asian economies appear to be insensitive to this shock at most quantiles.

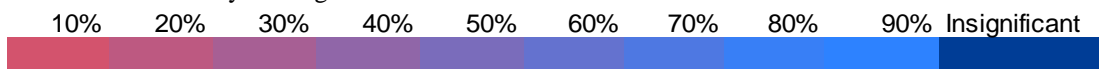
As for the sensitivity to changes in global risk aversion, red indicates high risk of outflows amid heightened global risk aversion, and blue and navy blue respectively indicate low and zero risk (Chart 3). The heat map shows that developed economies are generally "safer" with mostly blue cells, whereas a cluster of red cells appear among EMEs at extremely low quantiles. This indicates that in the worst-case scenario, bond markets in EMEs face more sizable outflows compared with developed markets. Among EMEs, however, emerging Asian economies are more resilient to changes in global risk aversion that, at the same quantile, the size of outflows is *ceteris paribus* smaller for emerging Asian economies than for other EMEs. This characteristic tends to put emerging Asia closer to the category of developed markets.

In addition to US monetary stance and global risk aversion, we also examine the autocorrelation of fund flows, which helps to depict whether an inflow (outflow) is more likely to lead to more inflows (outflows), *ceteris paribus*. This autocorrelation is captured by the coefficients of the one to three-month lagged fund flows. Chart 4 plots the coefficient of the one-month lagged fund flow estimated at different quantiles, with red denoting a higher autocorrelation and blue a lower autocorrelation. Since all of the coefficients are positive numbers, the coefficients represented by red cells at the extremely high or low quantiles are most destabilising, as they indicate self-reinforcing trends amid significant inflows or outflows. In the case of emerging Asia, persistent fund flow is more likely to appear at higher quantiles.

Chart 2: Heat map of sensitivity to FFR in post-crisis period at different quantiles



Note: 1. Economies are ranked by their sensitivity estimated in the OLS model.
 2. Colour scale is according to percentile of coefficients as shown below. As all significant coefficients are negative, the lower percentile corresponds to higher sensitivity and higher risk of outflows amid rate hikes.



3. Names of developed economies are highlighted in blue and emerging Asian economies in red.

Chart 3: Heat map of sensitivity to VIX in post-crisis period at different quantiles



Note: 1. Economies are ranked by their sensitivity estimated in the OLS model.
 2. Colour scale is according to percentile of coefficients as shown below. As all coefficients are negative, the lower percentile corresponds to higher sensitivity and higher risk of outflows during risk-off periods.

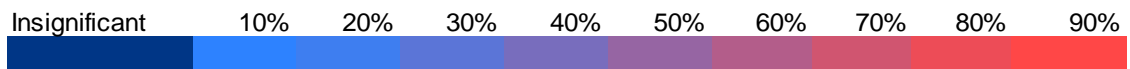


3. Names of developed economies are highlighted in blue and emerging Asian economies in red.

Chart 4: Heat map of autocorrelation in post-crisis period at different quantiles



Note: 1. Economies are ranked by their sensitivity estimated in the OLS model.
 2. Colour scale is according to percentile of coefficients as shown below. As all coefficients are positive, the higher percentile corresponds to higher sensitivity and higher risk of destabilising funds flows.



3. Names of developed economies are highlighted in blue and emerging Asian economies in red.

V. CONCLUDING REMARKS

In general, our empirical findings suggest that bond fund flows have become more sensitive to changes in the US monetary stance and global risk aversion amid increasing financial globalisation after the GFC. This is particularly true for the bond fund flows to EMEs when compared to those to developed economies, reflecting the increasing participation of global investors in EME bond markets in search for yields, and the tendency of their investment decisions to be based on global factors. Among EMEs, those in emerging Asia are found to be among the least sensitive and demonstrate features similar to developed economies, possibly due to their better economic fundamentals compared to other EMEs. Their predominant use of fixed rate debt securities also makes them less vulnerable to rate hikes. Our findings suggest that global investors are now more able to distinguish among EMEs instead of treating their bonds as a single asset class. While policymakers in some of the emerging Asian economies may be relieved that the risk of large outflows amid deterioration of global financial conditions is not as high as for other EMEs, they should be vigilant about the risk of large inflows.

REFERENCES

- Audigé, H. (2014). *Net flows to emerging markets' funds and the US monetary policy after the subprime crisis* (No. 2014-23). University of Paris West-Nanterre la Défense, EconomiX.
- Balakrishnan, R., Nowak, S., Panth, S., & Wu, Y. (2013). Surging capital flows to emerging Asia: facts, impacts and responses. *Journal of International Commerce, Economics and Policy*, 4(02), 1350007.
- Brana, S., & Lahet, D. (2010). Determinants of capital inflows into Asia: The relevance of contagion effects as push factors. *Emerging Markets Review*, 11(3), 273-284.
- Chan, E., Chui, M. K., Packer, F., & Remolona, E. M. (2012). Local currency bond markets and the Asian Bond Fund 2 initiative. *BIS paper*, (63f).
- Fratzscher, M. (2012). Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics*, 88(2), 341–356.
- Forbes, K. J., & Warnock, F. E. (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics*, 88(2), 235-251.
- Förster, M., Jorra, M., & Tillmann, P. (2014). The dynamics of international capital flows: Results from a dynamic hierarchical factor model. *Journal of International Money and Finance*, 48, 101-124.
- Ghosh, A. R., Ostry, J. D., & Qureshi, M. S. (2016). When do capital inflow surges end in tears?. *The American Economic Review*, 106(5), 581-585.
- Hui, C. H., Genberg, H., & Chung, T. K. (2011). Funding liquidity risk and deviations from interest-rate parity during the financial crisis of 2007–2009. *International Journal of Finance & Economics*, 16(4), 307-323.
- IMF (2017). *People's Republic of China Hong Kong Special Administrative Region: Staff Report for the 2016 Article IV Consultation Discussions*. International Monetary Fund.

Koepke, R. (2015). *What Drives Capital Flows to Emerging Markets? A Survey of the Empirical Literature*. University Library of Munich, Germany.

Koenker, R. & Bassett, G. (1978). Regression quantiles, *Econometrica*, 46(1), 33-50.

Milesi-Ferretti, G. M., & Tille, C. (2011). The great retrenchment: international capital flows during the global financial crisis. *Economic Policy*, 26(66), 289-346.

Mishra, P., Moriyama, K., & N'Diaye, P. (2014). Impact of Fed tapering announcements on emerging markets. *IMF Working Paper*, WP/14/19.

Rey, H. (2015). Dilemma not trilemma: the global financial cycle and monetary policy independence. *National Bureau of Economic Research*, No. w21162.

S&P Global (2016). If credit spreads hit crisis levels, U.S. corporates would fare better than those in the emerging markets. *S&P Global Market Intelligence: Scenario Analysis*.

Taylor, J. B., & Williams, J. C. (2009). A black swan in the money market. *American Economic Journal: Macroeconomics*, 1(1), 58-83.

Wong, A. Y-T., & Fong, T. P. W. (2011). Analysing interconnectivity among economies. *Emerging Markets Review*, 12(4), 432-442.

Wu, J. C., & Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3), 253-291