Impacts of Benchmark-Driven Investment on Volatility and Connectivity of Emerging Market Capital Flows

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Abstract

Recent research finds that benchmark-driven investment has increased markedly since the global financial crisis, a phenomenon that has arguably led to more volatile capital flows and increased vulnerability for emerging markets. We investigate how far this is true by examining the contribution of benchmark-driven investment to the volatility of foreign portfolio flows of emerging markets, focusing on equity flows, and the sensitivity of benchmark-driven investment to factors that tend to have an influence on the global economy or emerging markets. Interestingly, we find that benchmark-driven-investment-related flows are generally less volatile, thus having an effect of reducing, rather than increasing, the overall volatility of foreign portfolio flows. However, our results also show that they are more interconnected with each other due possibly to their higher sensitivity to global and emerging-market-related factors, supporting the notion that their rapid growth could make emerging markets more vulnerable in times of extreme market adversity, as sudden and simultaneous withdrawal of portfolio flows would potentially expose them to greater risks of external financing or balance of payment difficulties.

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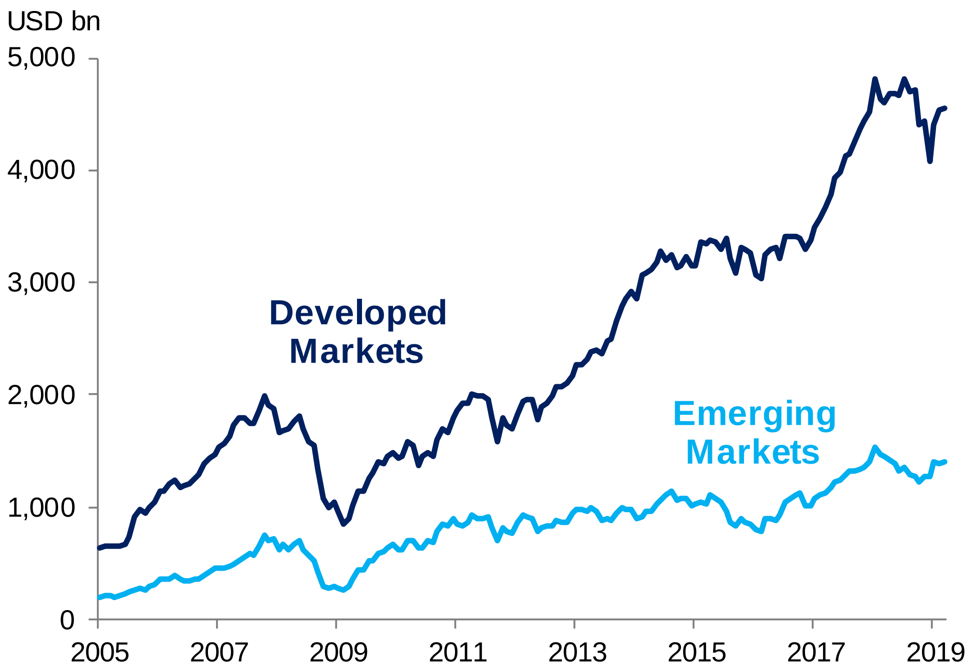
1. Introduction

Over the past decade, international financial integration has intensified, leading to a considerable increase in cross-border portfolio flows globally. To a significant extent, the increase is attributable to the growing popularity of benchmark-driven investment funds, especially those invested in a group of countries (or markets) with their investment performance benchmarked to some widely monitored global or regional indexes.[1] For example, benchmarked equity funds destined for developed markets amounted to only USD855 billion shortly after the global financial crisis and those for emerging markets (EMs) USD263 billion.[2] In early 2019 they surged four folds to USD4.5 trillion and USD1.4 trillion respectively (Chart 1).

Chart 1: Assets following global/regional benchmark equity indices in DMs and EMs



Source: EPFR.

For the investor, a major advantage of benchmark-driven investment funds is the benefit of having a diversified portfolio compared to investing in individual markets, while being able to tap the growth potential of a targeted group of economies. For many countries, especially the EM economies, the funds can bring in foreign investors whom they would not be able to attract or reach out to otherwise, thereby facilitating the establishment of a more diverse investor base, which is beneficial to long-term growth and stability. However, these benefits cannot be harnessed without a cost due to the fact that the assets in these portfolios tend to be treated as one asset class.

[1] As a result, the IMF (2019) defines benchmark-driven investment funds as those funds whose portfolio allocation across markets is guided by the country weights in a benchmark index.

[2] Figures are calculated as the estimated allocation in developed markets (DMs) and emerging markets (EMs) from global and regional funds included in Emerging Portfolio Fund Research (EPFR).

As global and regional benchmark indexes are constructed by weighing the individual country indexes by their respective market capitalization, buying and selling assets in one of the countries often necessitates buying and selling assets in the other countries in the benchmark index concerned in proportion to the country weights. Any disproportional buying or selling will make the portfolio deviate from the benchmark index, resulting in tracking risk that the investment manager would try to minimize while pursuing active return.[3] Hence, investment decisions of these funds tend to be dictated by considerations of the prospects of all the markets in the portfolio taken as a whole, rather than those of the markets individually. As a result, these portfolio flows could occur to a country even when they are unjustifiable by the country's economic fundamentals. This therefore concerns policymakers.

In its latest Global Financial Stability Report, the IMF (2019) alleges that the increase in benchmark-driven investment funds has made portfolio flows more volatile globally in recent years. Moreover, using bond market fund flows as an example, since these funds are more sensitive to global factors and factors that tend to affect EMs, their growing popularity also makes EMs more vulnerable. However, the Report only provides estimates supporting the observation about the rapid growth of these funds as a share of total cross-border portfolio investment. It runs short of proving the validity of the allegation. Hence, this papers aims to tackle two main research questions. First, would the increase in benchmark-driven investment make equity portfolio flows more volatile? Second, is benchmark-driven investment more sensitive to global and common EM factors? Interestingly, our results show that despite the fact that benchmark-driven equity investment could arguably lead to unjustifiable portfolio flows that would not exist otherwise, increase in benchmark-driven investment reduces, rather than increases, the volatility of portfolio flows as a whole. However, we also find that benchmark-driven investment tends to be more responsive to global and EM factors. Hence, it does pose a risk to financial stability to EMs, especially in times of extreme market adversity.

This paper focuses on equity foreign portfolio investment (FPI) flows for EMs. It is organized as follows. In Section 2, we explain how we define and estimate the benchmark-driven and unconstrained FPI flows for 15 EMs. In Section 3, we analyze the impacts of benchmark-driven FPI flows on the volatility of FPI flows. Section 4 examines the impacts of rising benchmark-driven investment on the connectivity of FPI flows among the EMs. Finally, in Section 5, we conclude this study with a brief discussion of the policy implications of the findings.

2. Estimating benchmark-driven and unconstrained FPI

In this section, let's put benchmark-driven foreign portfolio investment into perspective and look at its recent trend. Foreign investment is investment in a foreign country, hence it involves capital flowing from one country to another. The resulting foreign capital flows can be broadly divided into two types, foreign direct investment (FDI) and foreign portfolio

[3] The performance of the investment manager is measured by how well her portfolio does compared to the benchmark index, and hence tracking risk is the risk she takes in holding a portfolio with active positions that do not track the index.

investment (FPI). The former refers to the type of investment that can establish a lasting interest in and a significant degree of influence over an enterprise resident in another country, while the latter is mainly investment through holding financial assets of a foreign country such as equities and bonds. As FPI is more liquid and typically has a shorter investment horizon, the resulting flows are much more volatile. Since these financial assets are traded in international capital markets, FPI flows have a great influence on asset price fluctuations.

In light of this, two IMF economists investigate the role of benchmark-driven investors in FPI flows to the EM local currency government bond markets (Arslanalp and Tsuda, 2015) and find that the increasing share of benchmark-driven investors may render capital flows more sensitive to global shocks. In the Global Financial Stability Report (April 2019), the IMF also alleges that portfolio flows to EMs are increasingly affected by benchmark-driven investors, highlighting the risks of more volatile portfolio flows to EMs in a maturing credit cycle.

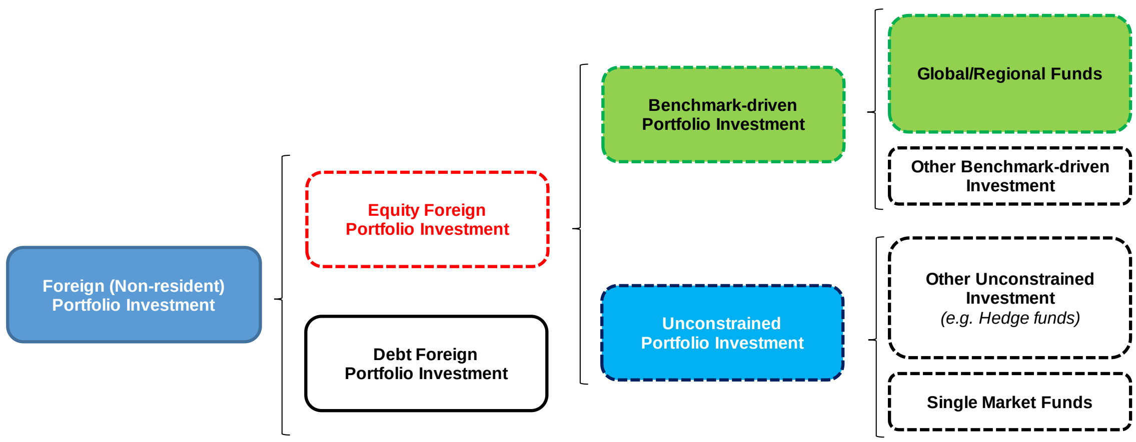
Chart 2 shows the breakdowns of FPI. We focus on equity FPI in this paper, complementing the study of bond FPI by Arslanalp and Tsuda (2015). To analyse the volatility of FPI, we need to have both the flow and stock data of FPI. The flow data are sourced from the Institute of International Finance (IIF) EM Portfolio Flows Tracker. They are monthly data, dating back to January 2001.[4] The stock data, often referred to as holdings, are taken from the derived portfolio investment liabilities in equities and investment fund shares from the IMF Coordinated Portfolio Investment Survey (CPIS) database.[5] These are annual data from 2001 to 2012 and biannual since 2013.

FPI can be broken down further into two categories, benchmark-driven and unconstrained. Benchmark-driven FPI refers to the FPI whose asset allocation is guided by country weights of a benchmark index, whereas unconstrained FPI is not subject to such asset allocation (IMF, 2019). It is important not to confuse benchmark-driven FPI with passive funds.[6] Passive funds obviously track their benchmarks in lockstep. However, even for active funds, which need not do the same, portfolio managers are also found to have a strong tendency to "hug" their benchmarks as tightly as possible to mitigate their career risk of short-term underperformance (Miyajima and Shim, 2014). Benchmark-driven FPI is mainly comprised of global and regional funds but includes funds under separately managed accounts whose performance is also often judged with reference to benchmarks designed by and agreed upon between the portfolio managers and clients concerned (J.P. Morgan, 2015).[7] Unfortunately, these investment vehicles, which technically are

[4] These IIF data are essentially the same as the IMF Balance of Payments data except that they are monthly rather than quarterly.
[5] Both CPIS and International Investment Position (IIP) data share the same concepts and valuation principles as detailed in the sixth edition of the Balance of Payments and International Investment Position Manual (BPM6). According to the IMF, any discrepancy between them is attributable to different data vintage and incomplete sectoral coverage in CPIS. We use the CPIS data because they cover some emerging markets that the IIP data do not.
[6] In fact, passive funds are a subset of benchmark-driven FPI.
[7] Separately managed accounts are individually tailored investments, the bulk of which is private banking. Funds under these accounts tend to follow their own benchmark indices (IMF, 2019).

benchmark-driven, cannot be included in benchmark-driven FPI in this study due to a lack of data. As a result, they are grouped under unconstrained FPI by default. This has the drawback of underestimating the size of benchmark-driven FPI and in fact the underestimation is not trivial.[8] However, this is unlikely to affect the thrust and results of our study given that the nature of other benchmark-driven investment is very similar to that of the global and regional funds.[9]

Chart 2: Breakdown of foreign (non-resident) portfolio investment



The benchmark-driven portfolio investment data are drawn from Emerging Portfolio Fund Research (EPFR).[10] To focus on benchmark-driven FPI flows from foreign portfolio investors, only those foreign-domiciled global and regional funds are taken into account.[11] These funds include the Africa Regional, Asia ex-Japan Regional, BRIC, Emerging Europe Regional, Europe ex-UK Regional, Europe Regional, EMEA Regional, Global, Global Emerging Markets, Global ex-US, Greater China, Latin America Regional, Middle East & Africa Regional, Middle East Regional, and Pacific Regional funds. The data, both stocks (referred to as net asset values by EPFR) and flows, are of monthly frequency, dating back to February 1996. Unconstrained FPIs mainly consist of hedge funds, which includes absolute return funds, and single market funds. These funds are unconstrained in the sense that buying and selling of the assets for them are not subject to country weight considerations.

[8] Assets allocated to EMs of regional and global funds amounted to $1.32 trillion as of June 2018, according to EPFR data. However, assets benchmarked to the MSCI EM Index suite exceed USD1.8 trillion as of June 2018. This means that the amount of benchmark-driven investment can be underestimated by more than 27% in our analysis. As a result, the proportions of benchmark-driven investments in total FPI holdings for individual EMs are underestimated by 11-19 percentage points.

[9] Interested readers can refer to Appendix B for a detailed discussion.

[10] As per EPFR estimates, their data cover around 76% of the exchange-traded funds and mutual funds globally as of Q1 2018 in terms of assets size.

[11] It is possible that domestic investors investing in foreign domiciled funds would ultimately end up with some exposures to their own domestic equity market. However, we believe these exposures are negligible.

By definition, total FPI holdings (TPH) of a market is the sum of benchmark-driven FPI holdings (BPH) and unconstrained FPI holdings (UPH) of the market:

$$TPH = BPH + UPH \tag{1}$$

and the total FPI flows of a market (TPF) is the sum of benchmark-driven FPI flows (BPF) and unconstrained FPI flows (UPF) of the market:

$$TPF = BPF + UPF \tag{2}$$

Based on Equations (1) and (2), we subtract the BPH and BPF from TPH and TPF respectively to obtain UPH (Chart 3A) and UPF (Charts 4A). We do not follow the approach proposed by Balston and Melin (2013) to decompose TPH by means of constrained least squares, as it has an overly strong assumption that unconstrained investors allocate capital based on the market capitalization of the markets concerned, which we find unrealistic.[12]

We base our definition for emerging markets on MSCI's classification as MSCI produces the popular and authoritative equity benchmark indexes.[13] There are a total of 26 EMs in the MSCI Emerging Market Index at the time of writing this paper but only 15 of them are covered in this study: Brazil, Chile, Hungary, India, Indonesia, Korea, Malaysia, Mexico, the Philippines, Poland, Qatar, South Africa, Taiwan, Thailand and Turkey. The rest are excluded for a number of reasons, e.g., data limitation, inadequate history of membership in the Index (see Appendix A for details). As the onshore Chinese equities (China A shares) were not included in the MSCI EM Index until June 2018, China is excluded in our analyses for EMs.[14] To match the frequency of the flows data, holding data is linearly interpolated into monthly frequency. The data are generally stable over time and, thus, the interpolation is reasonable and does not incur a material loss of information. As can be seen in Chart 3A, BPH has increased steadily in recent years, after sustained contraction pressure in 2009. Although the absolute asset size has sharply increased, the share of BPH has stabilised at around 30-40% of TPH (Chart 3B). Among individual EM economies, the share of BPH generally increases over time, with the average of the EMs covered in this study increasing from 28% in January 2005 to around 38% in December 2018 (Chart 3C).

Chart 3A: Benchmark-driven and unconstrained FPI holdings in EMs

[12] Balston and Melin (2013) decompose foreign holdings of local-currency government bonds into benchmark-driven and unconstrained parts by constrained least squares approach, restricting their sum to be the total foreign holdings. This is unrealistic as unconstrained investors such as hedge funds and professional individual investors often overweight or underweight a particular market compared with their benchmarks.

[13] According to [MSCI](), assets benchmarked to the MSCI EM Index suite exceed USD1.8 trillion as of June 2018. The MSCI EM Index suite is comprised of the MSCI EM Net Return Index, MSCI EM Total Return Index, MSCI EM Small Cap Index, MSCI EM Latin America Index, etc. Single country indexes are not included in the MSCI EM Index Suite.

[14] In fact, MSCI has included another kind of onshore Chinese equities, namely B shares, in the MSCI EM Index since September 1996. However, the weight of B shares in the MSCI EM Index is small and the market capitalizations of B shares are trivial compared with that of A shares. Therefore, the benchmark-driven FPI flows of China should be negligible before the inclusion of A shares in the MSCI EM Index.

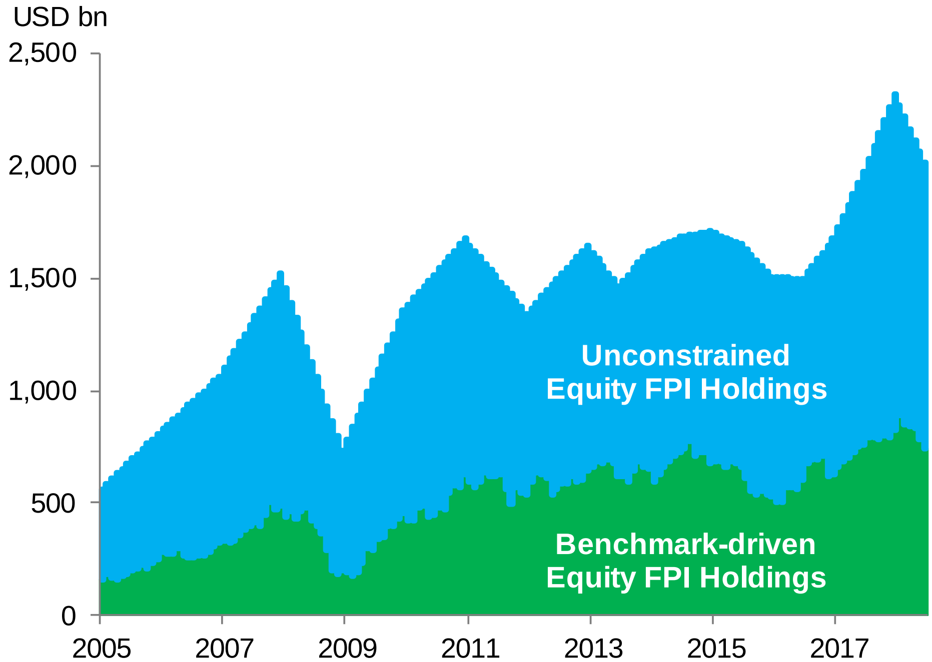


Chart 3B: Shares of benchmark-driven and unconstrained FPI holdings in EMs

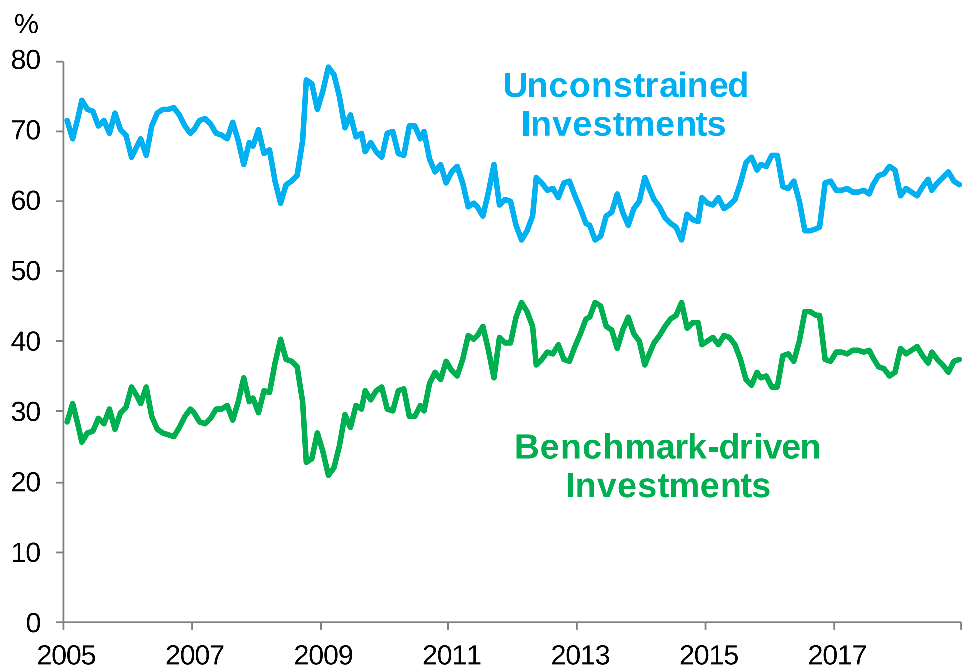


Chart 3C: Proportion of BPH in TPH by individual EMs

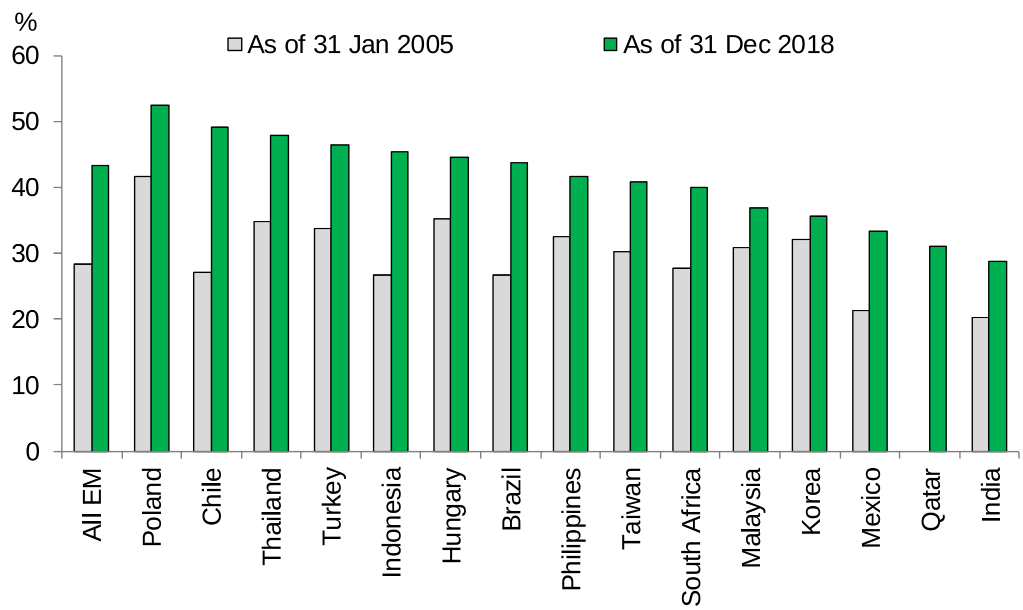


Chart 4A shows the cumulative BPF and UPF in EMs. It is found that foreign portfolio flows to EM equities are increasing but BPF are rising at lower pace compared with UPF. One may have a clearer idea while looking at the monthly foreign portfolio flows. Chart 4B shows monthly BPF and UPF to EMs as a percentage of BPH and UPH respectively in EMs. It can be seen that both benchmark-driven and unconstrained monthly equity FPI flows are quite steady at within -4% to 4% of their total holdings in the past decade.

Chart 4A: Cumulative TPF, BPF, and UPF in EMs

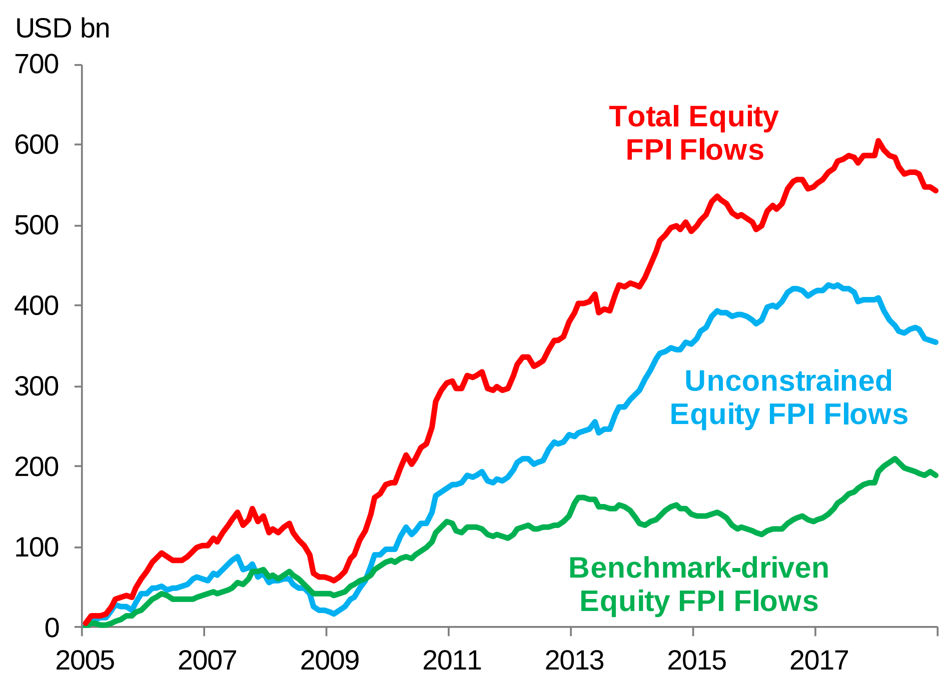
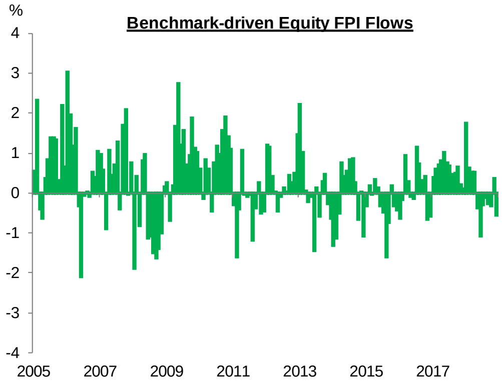
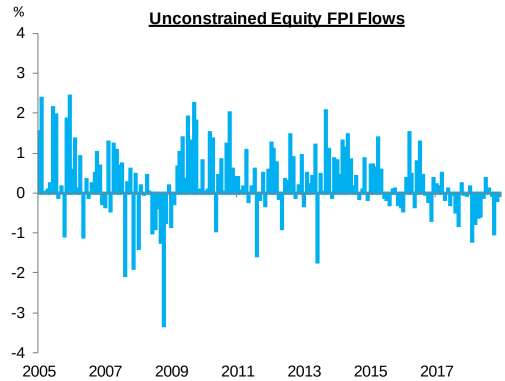


Chart 4B: Monthly BPF and UPF as a percentage of BFH and UPH in EMs





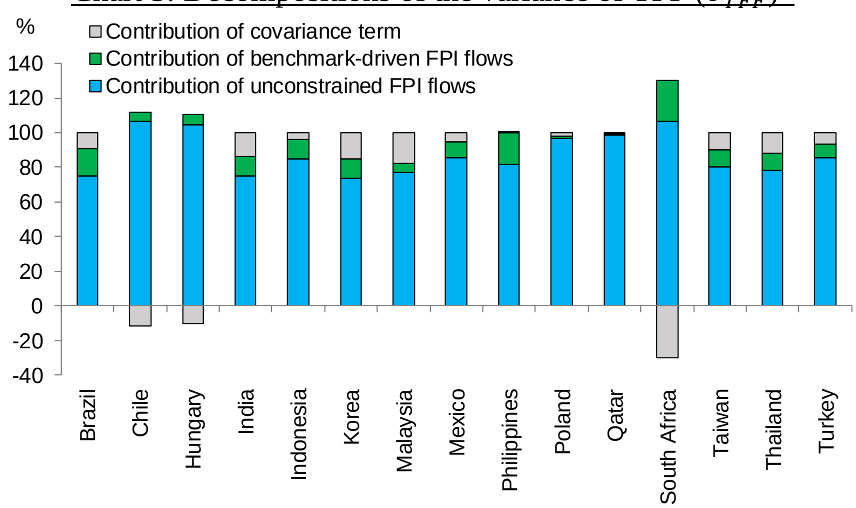
3. Impact of benchmark-driven FPI on volatility of FPI flow

In this section we analyse whether an increase in the share of BPH would increase the volatility of FPI flows. To do so, we first decompose the variance of TPF into the variance of BPF, the variance of UPF and twice the co-variance of the two:

$$\sigma_{TFF}^2 \equiv \sigma_{BFF}^2 + \sigma_{UFF}^2 + 2Cov(BPF, UPF) \tag{3}$$

where σ represents the standard deviation.[15] Based on equation (3), we compute the contributions of the variance of BPF and UPF as well as of their covariance term to the volatility of TPF in Chart 5. As can be seen, on average, the contribution of the variance of UPF dominates the variance of TPF, due partly to the fact that UPF accounts for a much greater proportion of TPF. However, it is uncertain as to whether the larger contribution of the variance of UPF is also attributable to UPF actually being more volatile.

Chart 5: Decompositions of the variance of TPF (σ_{TFF}^2)*



* The variance is estimated with monthly FPI flows data from 2010 to 2018.

To compare the dispersion between two sets of data with significantly different means, a common practice is to look at their coefficients of variation, i.e., the standard deviation

[15] In this paper, we use the method of standard deviations over a rolling window to estimate σ, which is a simple yet reliable approach to estimate capital flow volatility (Pagliari and Hannan, 2017).

relative to the mean (Pagliari and Hannan, 2017). Unfortunately, it makes no sense in the case of FPI flow data whose monthly means are often too close to zero that the level of measurement is not ratio scale (Herve Adbi, 2010).[16] Pagliari and Hannan (2017) point out that such close-to-zero means would render the coefficients of variation approaching infinity and profoundly sensitive to small variations in the means. Therefore, to facilitate comparison of volatility between the two types of FPI flows, we augment the coefficient of variation, replacing the mean of the type of FPI flows by the amount of the corresponding FPI holdings. We divide equation (3) by the square of TPH:

$$\frac{\sigma_{TPF}^2}{TPH^2} \equiv \frac{\sigma_{BPF}^2}{TPH^2} + \frac{\sigma_{UPF}^2}{TPH^2} + \frac{2Cov(BPF,UPF)}{TPH^2} \tag{4}$$

To have more meaningful interpretation, we manipulate equation (4) as follows:

$$\frac{\sigma_{TPF}^2}{TPH^2} \equiv \frac{BPH^2}{TPH^2}\frac{\sigma_{BPF}^2}{BPH^2} + \frac{UPH^2}{TPH^2}\frac{\sigma_{UPF}^2}{UPH^2} + 2\ \frac{BPH}{TPH}\frac{UPH}{TPH}\rho_{BPF,UPF}\frac{\sigma_{BPF}}{BPH}\frac{\sigma_{UPF}}{UPH}$$

which can be re-written as:

$$\theta_{TPF}^2 \equiv w^2\theta_{BPF}^2 + (1-w)^2\theta_{UPF}^2 + 2w(1-w)\rho_{BPF,UPF}\theta_{BPF}\theta_{UPF} \tag{5}$$

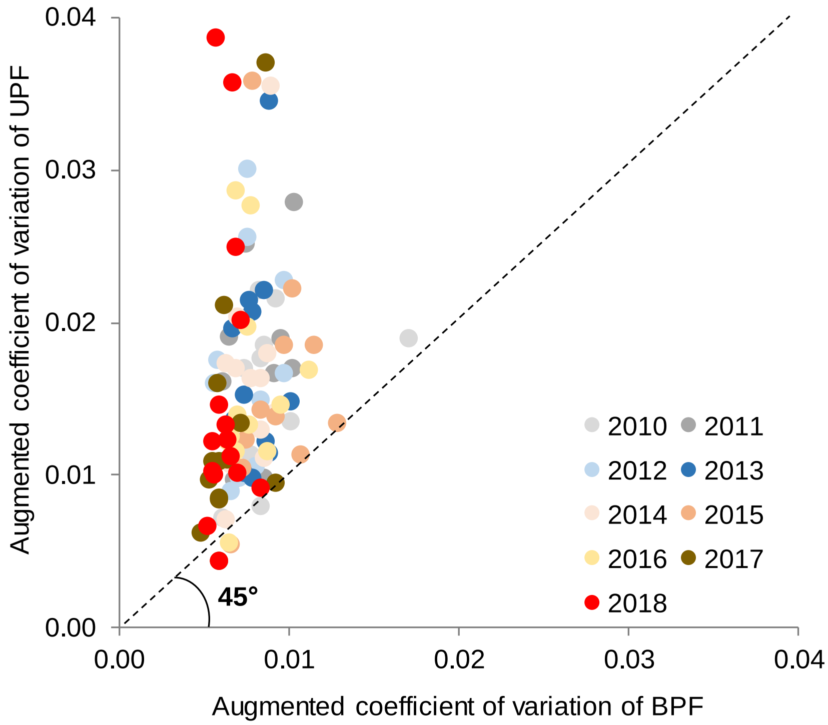
where θ denotes the augmented coefficient of variation, i.e., the standard deviation per dollar of holdings of the respective type of FPI, and w stands for the share of BPH in FPH. Equation (5) suggests that the volatility of TPF depends on (a) the volatilities of BPF and UPF and the correlation between them; and (b) the shares of BPH and UPH in TPH.

Chart 6 presents a scatterplot of θ_{UPF} against θ_{BPF}. Each dot denotes the average augmented coefficient of variation for an EM in a certain year. Dots for each year share the same colour. As can be seen, almost all the dots lie above the 45-degree line, suggesting that the volatility of UPF is generally higher than that of BPF. This result is fairly robust, given that there is no drastic change in the pattern from one year to another.[17] This implies that, other things being equal, faster growth of benchmark-driven investment is likely to reduce, rather than increase, the volatility of TPF.

Chart 6: Volatility of BPF versus volatility of UPF

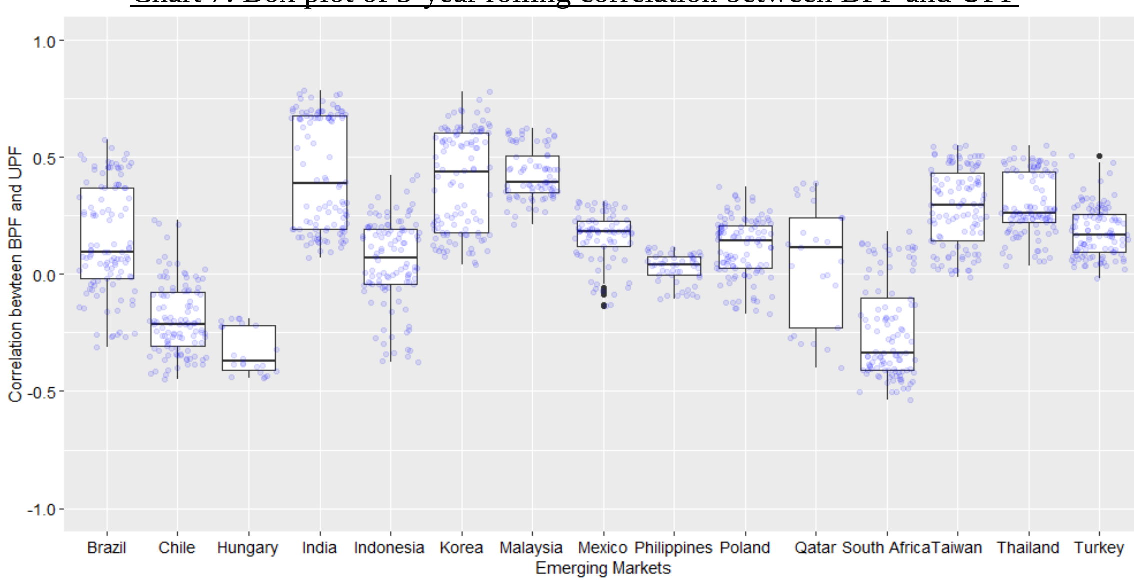
[16] An absolute zero is always implied by the ratio scale (Stevens, 1946). This means that a meaningful negative value does not exist. However, this is not the case for capital flows which always contain negative numbers indicating capital outflows.

[17] The standard deviation per dollar of holdings is estimated using data of 3-year window. For example, the standard deviation per dollar of holdings as of January 2010 is the standard deviation of monthly FPI flows within the period of February 2007 to January 2010 divided by the values of FPI holdings as of January 2010. We use period-end instead of period-average FPI holdings since the values of BPH in earlier period may be unrepresentative due to incomprehensive fund coverage of EPFR Global in early days.



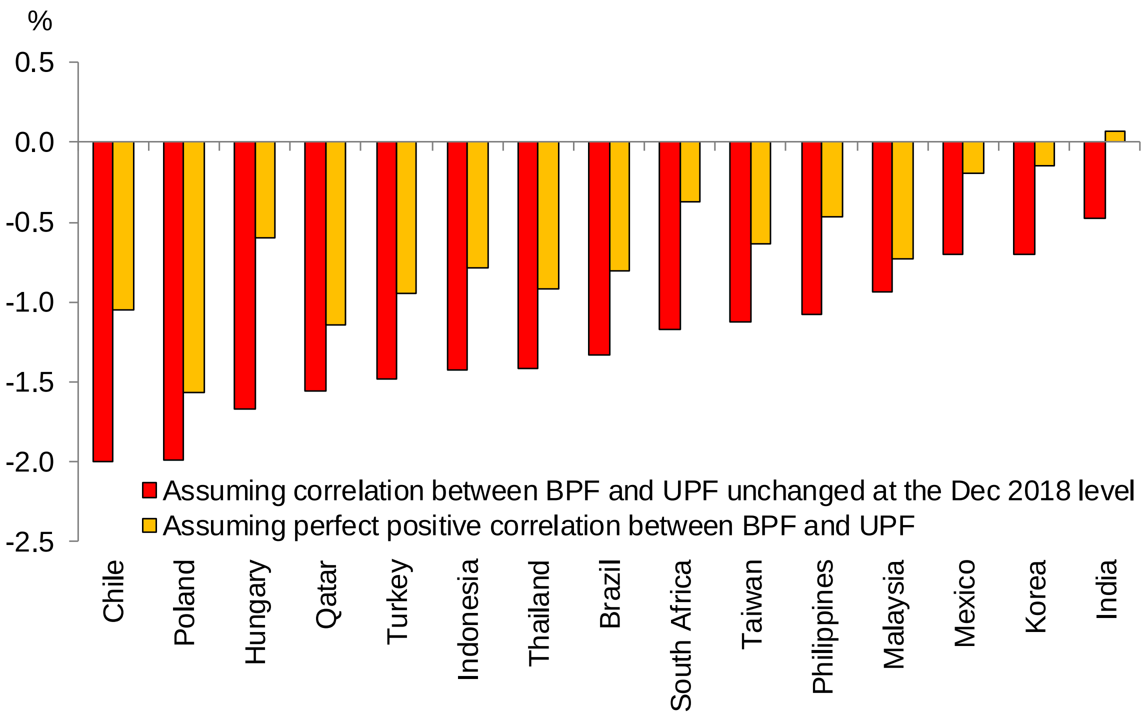
However, the covariance between BPF and UPF, i.e., the third term on the right hand side of equation (5), can make our argument untenable if $\rho_{BPF,UPF}$ is sufficiently large. Chart 7 depicts the distributions of the three-year rolling $\rho_{BPF,UPF}$ from January 2010 to December 2018 of individual EMs by box plots. We can see that $\rho_{BPF,UPF}$ can be quite unstable and high for some EMs. As a result, it is important that we take the covariance term into account when assessing whether an increment in w could reduce θ_{TPF}.

Chart 7: Box plot of 3-year rolling correlation between BPF and UPF



Therefore, to more precisely gauge how responsive θ_{TPF} is to the change in composition of TPH, we perform a sensitivity analysis taking the covariance term into account. Chart 8 shows how more or less volatile TPF would become in response to a change in the share of BPH as of December 2018, by assuming that θ_{BPF} and θ_{UPF} will stay at the contemporaneous levels estimated with the flows and holdings data in the past three years. The red bar measures the response assuming that the correlations of BPF and UPF of each individual markets remain unchanged as of December 2018.[18] For example, a one-percentage-point increase in w implies that the augmented coefficient of variation of TPF will decrease by two percent for Chile. The orange bar shows the response under the extreme scenario that BPF and UPF are positively perfectly correlated, the reduction in the volatility of total FPI flows is about one percent.[19] We find that for all the EMs covered by this study, an increase in the w always reduces θ_{TPF} with the only exception of India in the case of a perfect positive correlation between BPF and UPF.

Chart 8: Sensitivity of augmented coefficient of variation of TPF to one-percentage-point increment of w as of December 2018



One may argue that while the sensitivity analysis is sound, the estimated effects of increasing w on θ_{TPF} can turn out to be very different from what may actually happen. The reason is that not only can θ_{BPF}, θ_{UPF}, and $\rho_{BPF,UPF}$ change significantly from the contemporaneous levels over time, but their relationship can also evolve considerably.[20]

[18] The correlations as of December 2018 is estimated using data of 3-year window from January 2016 to December 2018.
[19] The percentage reduction in the augmented coefficient of variation of TPF is calculated by comparing the new θ_{TPF} under new w and the original θ_{TPF}.
[20] For instance, θ_{BPF}, θ_{UPF} and $\rho_{BPF,UPF}$ can move in directions completely different with historical patterns as a result of the change in compositions of the MSCI EM Index.

To see whether faster growth of benchmark-driven FPI would really reduce the volatility of TPF, we have to allow some variations in, and random combinations of, θ_{BPF}, θ_{UPF}, and $\rho_{BPF,UPF}$. To do so, we conduct a Monte Carlo simulation to estimate the probability of $\partial(\theta_{TPF}^2)/\partial w < 0$ under certain assumptions.[21] Before that, we derive $\partial(\theta_{TPF}^2)/\partial w$ by partially differentiating equation (5) with respect to w:[22]

$$\frac{\partial(\theta_{TPF}^2)}{\partial w} \equiv 2w\theta_{BPF}^2 - 2(1-w)\theta_{UPF}^2 + 2(1-2w)\rho_{BPF,UPF}\theta_{BPF}\theta_{UPF}$$

By assuming that θ_{BPF}, θ_{UPF}, and $\rho_{BPF,UPF}$ take on some values, we can calculate the value of the partial derivative when w is evaluated at w':

$$\left.\frac{\partial(\theta_{TPF}^2)}{\partial w}\right|_{w=w'} \equiv 2w'\theta_{BPF}^2 - 2(1-w')\theta_{UPF}^2 + 2(1-2w')\rho_{BPF,UPF}\theta_{BPF}\theta_{UPF} \qquad (6)$$

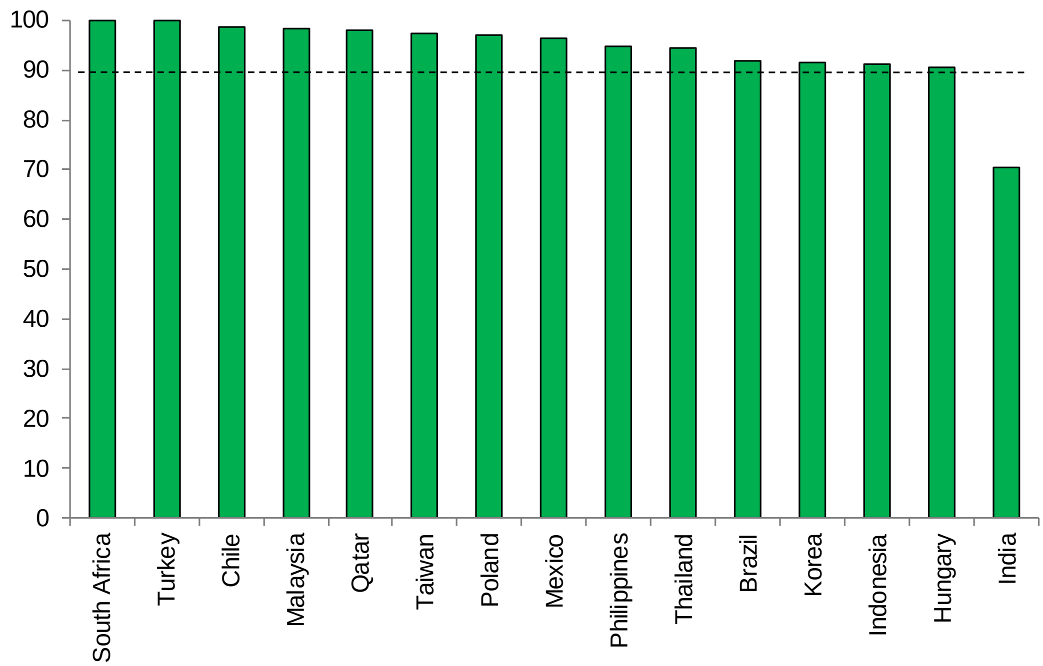
To create random combinations of θ_{BPF}, θ_{UPF}, and $\rho_{BPF,UPF}$, we assume that they are independent and randomly draw samples from their respective marginal distribution. However, we cannot simply assume that these parameters are normally distributed as some of the distributions are far from normal. For instance, as can be seen in Chart 7, $\rho_{BPF,UPF}$ of India appears to follow a bimodal distribution. As a result, we resort to a non-parametric method called kernel density estimation (KDE) to estimate the probability density function of the three parameters of individual EMs. What KDE does is to try to figure out the probability density function of the variables from the observed data without any assumptions on the underlying distribution. With the KDE estimated probability density function for the three parameters, we can back out their cumulative distribution function and conduct a simulation to generate random values of the partial derivatives.[23] Chart 9 presents the estimated probability of $\partial(\theta_{TPF}^2)/\partial w < 0$, given that w equals the value as of December 2018. Interestingly, the result is consistent with that of the earlier sensitivity analysis in that faster growth of benchmark-driven investment can reduce the volatility of TPF most of the time for all EMs except India.

Chart 9: Probability of $\partial(\theta_{TPF}^2)/\partial w < 0$ through simulation for individual EMs

[21] The Monte Carlo simulation is a simulation that obtains numerical results based on repeated random sampling (Raychaudhuri, 2008).

[22] Using the method of linear approximation, the estimated effect of a one-percentage-point change of w on θ_{TPF}^2 is the partial derivative divided by 100.

[23] Firstly, we use KDE to estimate the PDF (and back out the CDF) of θ_{BPF}, θ_{UPF}, and $\rho_{BPF,UPF}$ of individual EMs. After that, one million samples of the three parameters are created by using the inverse transform method, which converts random numbers 0 to 1 drawn from the standardized uniform distribution to random values for the three parameters through their respective inverse CDF (Raychaudhuri, 2008). Based on equation (6) and the random samples of θ_{BPF}, θ_{UPF}, and $\rho_{BPF,UPF}$ drawn, we can derive one million samples of the partial derivative, by assuming that w equals to the value as of December 2018.



There are several possible explanations for the phenomenon of the generally lower volatility of benchmark-driven FPI flows. One possible reason is the popularity of core-satellite investment approach, in which investors construct their portfolios with a stable core of long-term investments and a periphery of shorter-term holdings (Vanguard, 2010). Global or regional benchmark-driven funds could be a good choice for the core part due to its diversified nature while other hedge funds and single market dedicated funds could be potential candidates for the satellites. With this kind of strategy, investors will trade the core part less actively than the satellite part, resulting in less volatile capital flows to those benchmark-driven investment vehicles. Brandao-Marques et al. (2015) also show that global funds are more stable sources of capital flows than dedicated EM funds, albeit their fund managers can reallocate their portfolios completely away from EMs.[24]

4. Impact of benchmark-driven FPI on connectivity of FPI flows among EMs

A possible concern for policymakers about the rapid growth of benchmark-driven investment is that it may be potentially damaging to global financial stability. To the extent that assets in benchmark-driven funds destined for EMs are treated as one asset class, the FPIs across EMs would tend to move together. This is despite the fact that these economies may face vastly different macroeconomic conditions. The resulting increase in connectivity among their FPI flows potentially heightens the risk that EMs simultaneously experience external financing difficulties when foreign investors rush for the exit in times of stressful market conditions. The global financial crisis probably provides the best testimony to this. In the quarter after the collapse of Lehman Brothers, both benchmark-driven investment and unconstrained investment fell considerably but the fall in the former was much steeper

[24] Brandao-Marques et al. (2015) attributed the phenomenon to the difference in the behaviour of the ultimate investors.

(Charts 3A and 3B). In this section, we examine (i) how correlated BPFs and UPFs are between EMs; (ii) the extent to which BPFs and UPFs of different EMs would move together; and (iii) how responsive BPFs and UPFs are to changes in global or common EM factors.

Pairwise correlation

We estimate the average pairwise correlation of the BPFs and UPFs between individual EMs from 2016 to 2018. Due to data availability considerations, we focus on these three years so that the results can be presented neatly. However, the picture would not look discernibly different if we cover the whole sample period or use another sub-period. In Charts 10A and 10B, each dot represents an EM with its size proportional to the amount of its holdings of the respective type of FPI of the country. For example, Korea and India has the greatest amount of BPH and UPH respectively. The colour of the dot denotes the geographical region the EM belongs: green for Asia, orange for EMEA and blue for Latin America. In Chart 10A the lines connecting each pair of EMs represent their correlation, with black, dark grey and light grey representing the correlation coefficient falling in the range of 99-100%, 95-99%, and 90-95% respectively. In Chart 10B, only pairs of UPFs with a correlation coefficient higher than 50% are connected by dark grey lines.

Chart 10A: Pair-wise correlation between BPFs in EM markets (2016 to 2018)

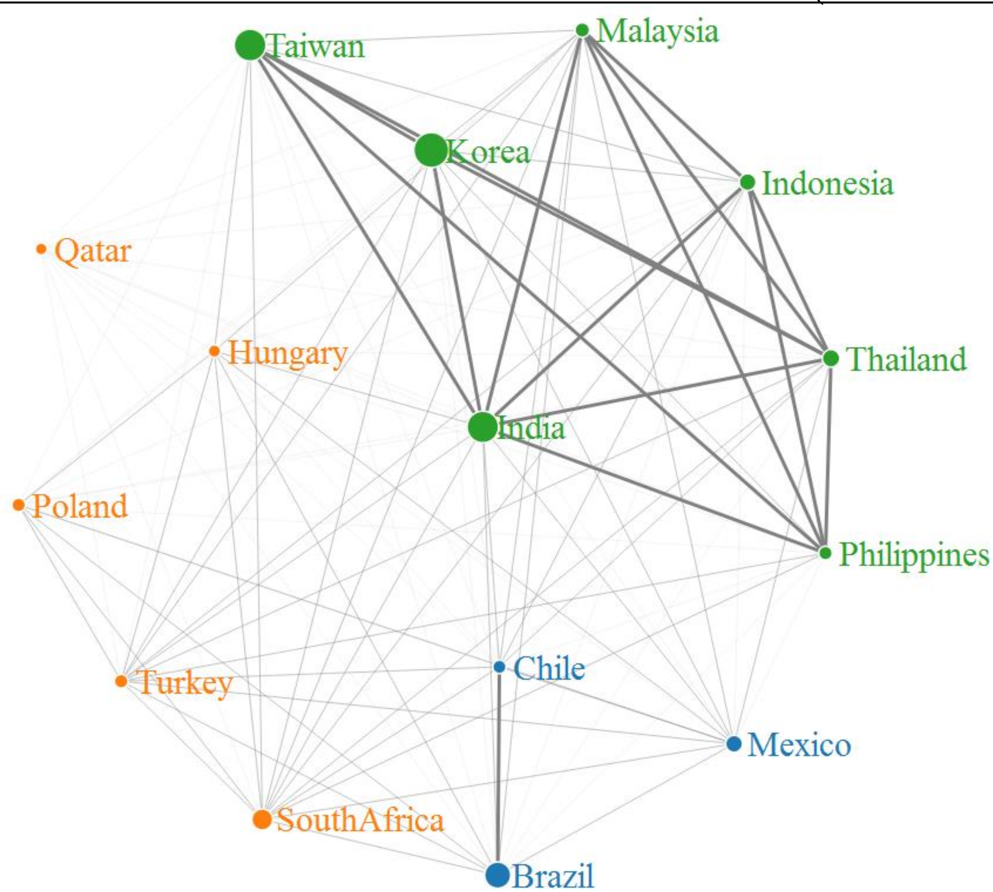


Chart 10B: Pair-wise correlation between UPFs in EM markets (2016 to 2018)

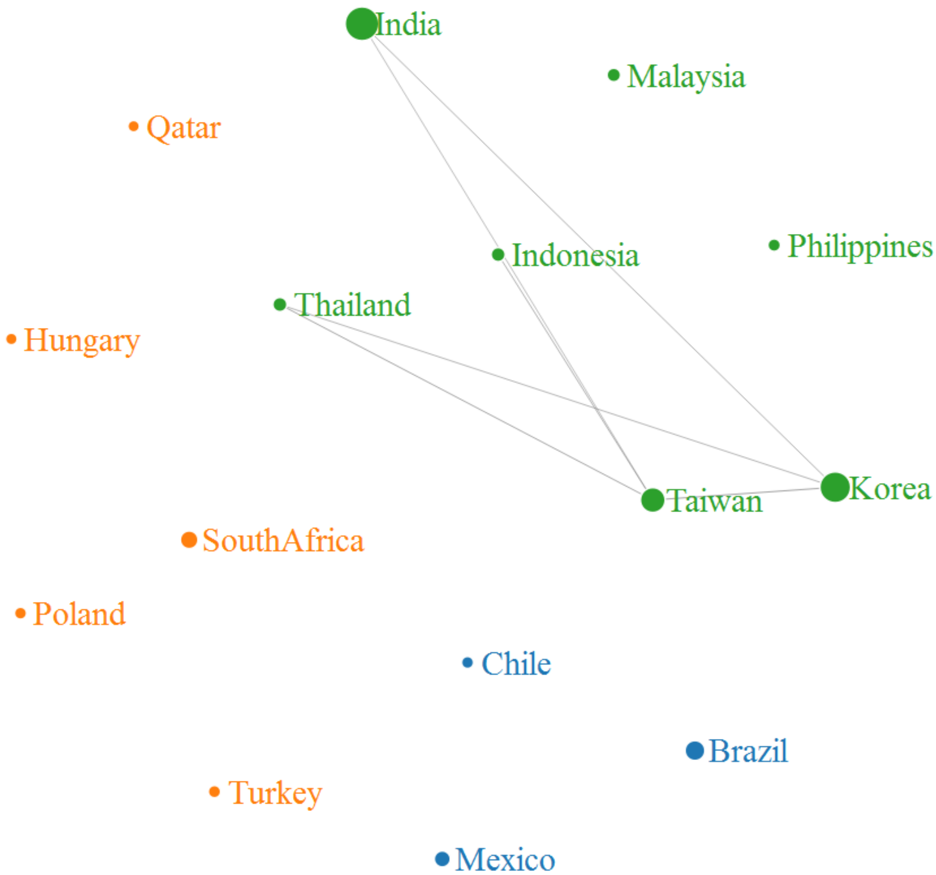


Chart 10A shows that benchmark-driven flows of individual EMs are highly correlated not only between EMs within the same region, but also between EMs from different regions. For example, the correlation between benchmark-driven FPI flows of Indonesia and Qatar is as high as 93.3%, despite the fact that the economic and financial linkages between these two economies are rather weak.[25] One possible explanation for such high correlation between their BPFs is that benchmark-driven investors tend to treat EMs as one asset class and focus on common factors that affect EMs as a whole (IMF, 2019). Hence, one may argue that a larger share of BPF in TPF increases the risk of excessive inflows or outflows unrelated to countries' fundamentals, hence causing a destabilizing effect to the economy.

Absorption ratio

[25] According to the Observatory of Economic Complexity, Indonesia's (Qatar's) exports to Qatar (Indonesia) make up only 0.04% (1.60%) of its total exports in 2017. Imports of Qatar (Indonesia) from Indonesia (Qatar) share only 0.34% (0.54%) of its total imports. Base on the Coordinated Portfolio Investment Survey, Qatar's portfolio investments in Indonesia only accounts for 0.001% of total foreign portfolio investments in Indonesia as of June 2018 (the analogous data for Indonesia's portfolio investments in Qatar is not available).

To gauge how similar the risk exposures of BPFs and UPFs among EMs are, we follow Billio et al. (2012) to estimate the absorption ratio for these two types of FPI flows based on principal component (PC) analysis, a technique in which two or more time series are decomposed into orthogonal factors of decreasing explanatory powers known as PCs.[26] If the time series are highly linked, a small number of PCs can explain a large proportion of their variance, which is the absorption ratio. Kritzman et al. (2011) uses this ratio to measure of how synchronized they move together, which arguably reflects how similar their risk exposures are. The higher the ratio, the more similar are the risk exposures.

Chart 11 shows the three-year rolling absorption ratios of PC1 for the BPFs and UPFs of the EMs from 2016 to 2018. The ratio of the BPFs falls within the range of 85-95% and that of the UPFs in a lower band of 20-40%, suggesting that the benchmark-driven FPIs are subject to much more similar risk exposures compared to the unconstrained FPIs. To show the proportion of the variance explainable (or eigenvalues) of each principal component in descending order, we present a scree plot of the PCs of the BPFs and UPFs of the EMs estimated using the 2016-2018 data in Chart 12 (Kellow, 2006). As can be seen, the proportion for the BPFs falls sharply from PC1 to PC2 and then levels off, while that for the UPFs reduces gradually. These results again lend support to the argument that BPFs of EMs share a lot more similar risk exposures compared to UPFs.

Chart 11: Absorption ratios of BPFs and UPFs in EMs

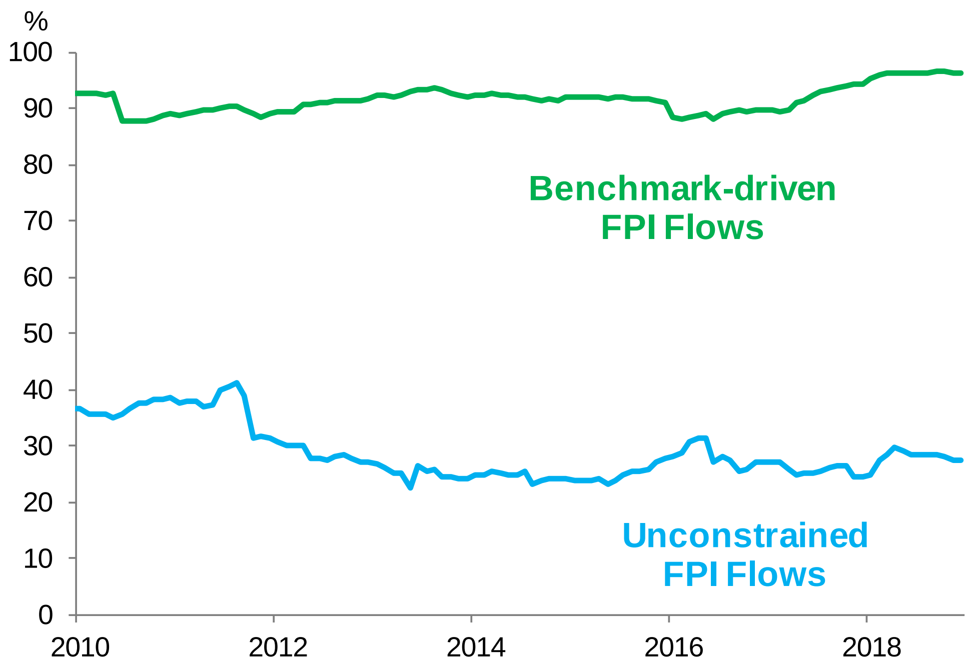
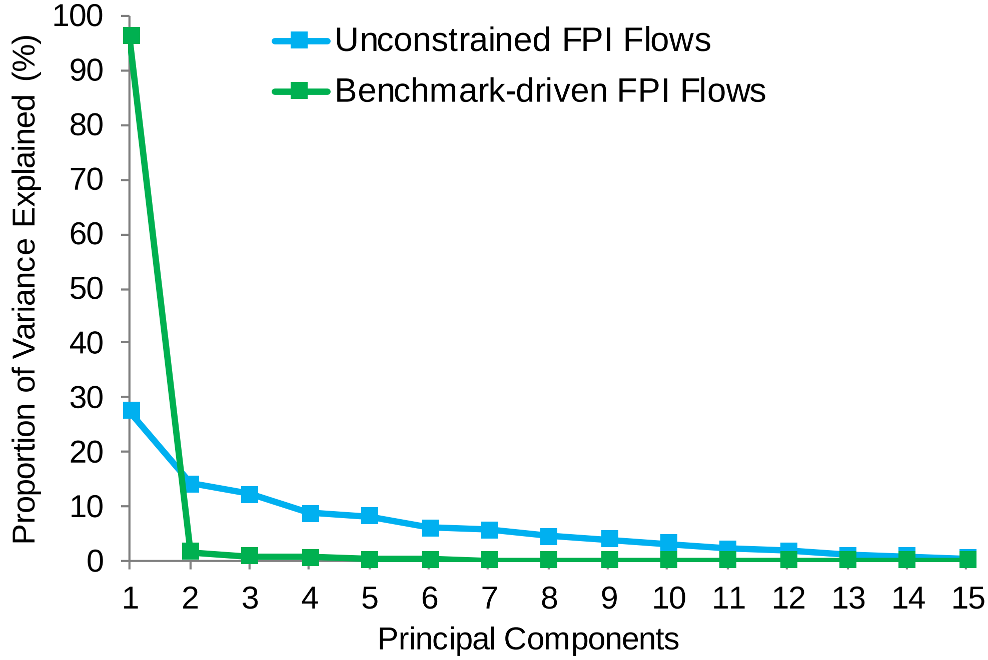


Chart 12: Scree plot of BPFs and UPFs in EMs

[26] Billio refers the ratio of the risk associated with the first *n* PCs to the total risk of the asset returns of a sample of financial institutions to as the cumulative risk fraction, which is essentially the same as the absorption ratio introduced by Kritzman et al. (2011).

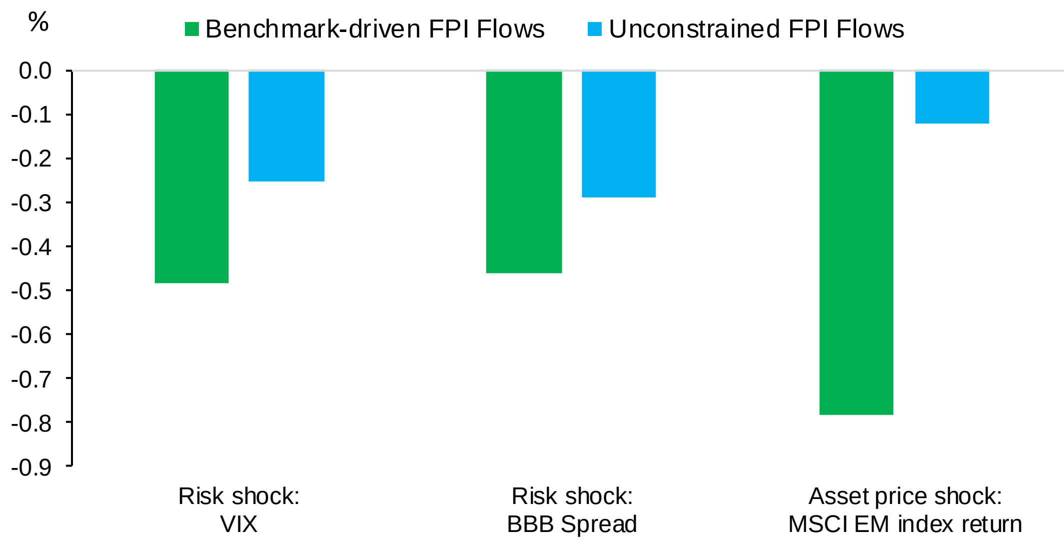


Global and common EM factor sensitivity

To measure the response of the BPF and UPF of the EMs to changes in global or EM common factors, we use the VIX and BBB yield spread to proxy global risk aversion and the return of the MSCI EM Index to proxy EM asset prices. The response is assessed in terms of the average movements of the BPF and UPF under three extreme scenarios during 2010 to 2018: (i) while the monthly change of VIX is higher than its 90th percentile; (2) while the monthly change of BBB spread is higher than its 90th percentile; and (3) while the monthly return of the MSCI EM Index is lower than its 10th percentile.

In Chart 13 the green and blue bars are the sensitivities of the BPF and UPF to the external shocks respectively, which are estimated by comparing the period-average flows with the extreme-scenario flows. As can be seen, the green bars are much higher than the blue bars under the three extreme scenarios, suggesting that the BPF are more sensitive to the global or EM common shocks than the UPF. When the monthly change of VIX exceeds 4.9 percentage points, the average monthly BPF of the EMs is estimated to fall by around 0.49% of BPH, almost double the estimated 0.25% of their unconstrained counterpart. The results are of the similar flavour when sharp changes in the BBB yield spread and MSCI EM index are used as extreme scenarios.

Chart 13: Conditional means of BPF and UPF as a percentage of BPH and UPHs corresponding to different external shocks



5. Conclusion and policy implications

It is alleged that rapid growth of benchmark-driven investment may be a source of concern for global financial stability and especially for EMs as it makes portfolio flows more volatile and EMs more vulnerable to negative shocks. First of all, our estimates show that benchmark-driven investment has increased markedly over the past one and half a decades but so has unconstrained investment. As far as equity is concerned, the former has risen as a share of the total FPI relative to the latter but the rise occurred mainly between 2000 and 2012. Since the beginning of 2013, the share has been fairly stable.

True, if benchmark-driven investment increases portfolio flow volatility and EM vulnerability, and if the growth of benchmark-driven investment gathers pace again, then the concern is valid. However, our results suggest that BPF is actually less volatile than UPF and, taking their interaction into account, increase in BPF would most likely reduce the overall volatility of TPF rather than increasing it. Nonetheless, we find that benchmark-driven investment does promote connectivity among FPI flows of EMs, as BPFs are subject to changes in global or common EM factors to a greater extent. The risk facing EMs in light of the strong connectivity can best be exemplified by the global financial crisis during which benchmark-driven investment fell much more sharply than did unconstrained investment. Hence, the concern is real. The counterargument, however, is that EMs probably already pass the most stringent stress test, since a shock as severe and widespread as the global financial crisis does not cause balance of payments difficulties to any EM.

Be that as it may, both BPH and UPH are now four to five times of the level ten years ago and other capital flows have also grown tremendously. Whether or not EMs can still withstand a test of the same ferocity is questionable given their much higher degree of external orientation financially today. There may be a threshold beyond which some EMs may break down due to weaker economic fundamentals. And this threshold, which was perhaps not reachable, has become a possibility given the large volume of capital flows now. The effects or spillovers may also multiply as different types of capital flows interact and reinforce each other, e.g., bond and equity portfolio flows. These questions provide good food for thought for future research in this area.

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Appendix A: List of EMs included in MSCI Emerging Markets Index

Emerging markets	Included in our analyses?	Reason for exclusion
Brazil	Yes	
Chile	Yes	
Hungary	Yes	
India	Yes	
Indonesia	Yes	
Korea	Yes	
Malaysia	Yes	
Mexico	Yes	
Philippines	Yes	
Poland	Yes	
Qatar	Yes	
South Africa	Yes	
Taiwan	Yes	
Thailand	Yes	
Turkey	Yes	
China	No	*We cannot tease out the benchmark FPI flows to onshore Chinese equities only from the total benchmark FPI flows to all Chinses equities. Also, onshore Chinese equities (China-A shares) were not included the MSCI Emerging Markets Index until 2018.*
Argentina	No	*Recently reclassified to emerging markets status in 2019*
Colombia	No	*No data for equity portfolio flows from IIF*
Czech Republic	No	*Problematic values for UPH estimates*
Egypt	No	*No data for equity portfolio flows from IIF*
Greece	No	*Defined as advanced economy by IMF*
Pakistan	No	*Recently reclassified to emerging markets status in 2017*
Peru	No	*No data for equity portfolio flows from IIF*
Saudi Arabia	No	*Recently added to the MSCI EM Index in 2019*
Russia	No	*No data for equity portfolio flows from IIF*
United Arab Emirates	No	*No data for equity portfolio flows from IIF*

Source: MSCI.

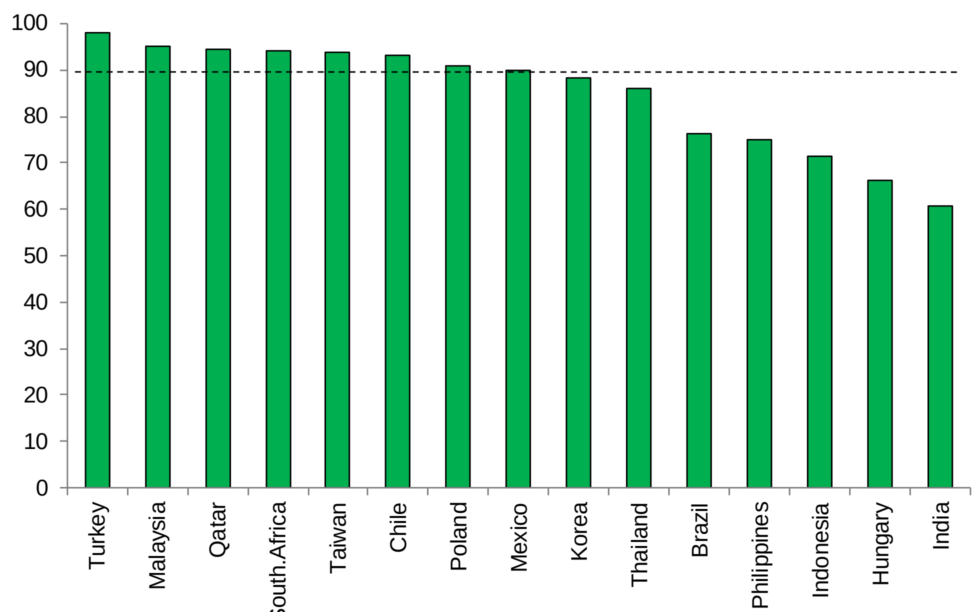
Appendix B: Why grouping other benchmark-driven investment under unconstrained investment will not affect the thrust and results of our study?

Since there is no data on benchmark-driven investment other than global and regional funds, other benchmark-driven investment is included in the unconstrained investment by default based on equations (1) and (2). A concern is whether this will affect the thrust and results of the subsequent analysis.

For the analysis of impact of benchmark-driven FPI on volatility, if we assume that the nature of other benchmark-driven investment is similar to that of global and regional funds, grouping other benchmark-driven investment which has lower volatility (as mentioned in Section 3) under unconstrained investment will only underestimate θ_{UPF}. Thus, our study is unlikely to be affected.

As mentioned in footnote 8, the amount of benchmark-driven investment is underestimated by 27%, which implies that the proportion of the benchmark-driven investment in total FPI holdings can be underestimated by 11-19 percentage points for individual EMs. Chart B1 shows the results of the simulation comparable to Chart 9, with w increasing by 11-19 percentage points for various EMs as a quick-and-dirty way to rectify the issue of underestimating BPH. As can be seen, the results of the simulation remain largely unchanged.

Chart B1: Probability of $\partial(\theta_{TPF}^2)/\partial w < 0$ through simulation for individual EMs with an increase of w by 11-19 percentage points for various EMs



By the same token, grouping other benchmark-driven FPI which has higher connectivity under unconstrained FPI will only drive up the connectivity of UPFs. However, the inflated connectivity of UPFs is still lower than their BPF counterparts by various measures. This again implies that classifying other benchmark-driven investment under unconstrained investment will not affect the thrust and results of our study.