Amundi
ASSET MANAGEMENT

Amundi Working Paper

WP-044-2014

November 2014

Portfolio Capital Flows: A Simple Coincident Indicator for Emerging Markets

Julien Moussavi, Ph.D. Student, Strategy and Economic Research - Amundi

Portfolio Capital Flows:

A Simple Coincident Indicator for Emerging Markets

Julien Moussavi

Strategy and Economic Research - Amundi

julien.moussavi@amundi.com

About the author

Julien Moussavi, Ph.D. Student, Strategy and Economic Research - Amundi

Ph.D. student in Finance at the Paris Dauphine University. Research Master's Degree in Economic and Financial Engineering at the Aix-Marseille School of Economics. Specialized Master's Degree in Finance at ENSAE ParisTech.

Emerging Markets Economist within the Amundi Research team, and working on Emerging Markets vulnerability, global excess liquidity and asset prices.

Abstract

The scarcity of up-to-date data is a meaningful constraint in the analysis of capital flows, especially for Emerging Markets (EMs). Indeed, the most commonly used source of cross-country data on capital flows is the Balance of Payments (BoP) statistics collected by the International Monetary Fund. Nevertheless, these data are available at low frequency and are usually published three to nine months later, notably for EMs. This delay is problematic for policy makers who need to calibrate appropriate policies in order to control the pernicious effects of volatile foreign capital flows, *i.e.*, economic and financial imbalances resulting from surges and/or sudden stops. To address this issue, we propose a simple coincident proxy to capture the gross portfolio capital flows towards EMs. This indicator is a metric of the current state of these portfolio flows and uses data from Emerging Portfolio Fund Research (EPFR) Global which covers net bond and equity flows. In an error correction framework, we propose to better capture foreign investors' sentiment. We find that the trend in EPFR data is a coincident indicator of BoP flows mainly in regional aggregates and large EMs. Finally, we build some Investor Sentiment indices that provide relevant information on EM asset returns.

Keywords: Emerging Markets, Balance of Payments, Portfolio Capital Flows, EPFR, Coincident Indicator, Investor Sentiment, Sudden Stop

JEL classification: E44, F21, F32, F37, G12

"Accommodating monetary policies could strain the capacity of emerging nations to absorb potentially large flows of capital and could lead to overheating and asset bubbles."

Christine Lagarde, IMF Managing Director
IMF and World Bank meeting, Tokyo, October 2012

1. Introduction

Since the early 2000s, capital flows to Emerging Markets (EMs) have risen massively. These large capital flows are theoretically profitable for the receiving countries. This huge increase is mainly explained by pull factors, *e.g.*, much stronger potential for economic growth and financial integration (Förster *et al.*, 2012). However, in practice, capital flow surges often end up in sudden stops and can carry some macroeconomic and financial imbalances, especially for EMs. These imbalances create challenges for policymakers and asset managers (IMF, 2007 and 2011a; Magud *et al.*, 2011; Forbes and Warnock, 2012). Since the global financial crisis of 2007-08, major central banks in Developed Markets (DMs) have considerably eased their monetary policies and provided some excess liquidity. This global excess liquidity revived international investors' risk appetite and willingness to search for yield behaviour, *i.e.*, push factors (Fratzscher, 2012). Since then, capital flows from DMs to EMs have bounced back (Fratzscher *et al.*, 2012) but, compared to pre-crisis waves of inflows, the post-crisis surge is characterised by an increasingly important part of portfolio flows (Calvo *et al.*, 1996; Edwards, 2000). Moreover, the shift from foreign direct investments and cross-border bank lending to- wards portfolio flows seems to be structural in nature and implies some volatility (IMF, 2011a and 2011b; Broner *et al.*, 2013). These risks are mainly present in Emerging Asia and Latin America (Kaminsky and Reinhart, 1999; Berthaud *et al.*, 2011; IMF, 2011b; Ahmed and Zlate, 2013). Over and above, monetary policy tightening is unavoidable in DMs in the medium term and the economic outlook in EMs turns out to be weaker than before, thus exacerbating the recent issues even more.

The post-crisis capital flow bonanza raises fears about the emergence of bubbles in asset prices, potential currency crises and the excessive growth of foreign exchange reserves. Furthermore, the last surge in capital flows is more volatile than ever. This volatility is driven by the fickleness of foreign investors' sentiment, mostly in portfolio flows which are the most volatile type of capital flows. In addition, the Balance of Payments (BoP) capital flows, collected by the International Monetary Fund (IMF), are the most commonly used source of cross-country data but BoP data have two major drawbacks: the data are (i) available at low frequency, *i.e.*, quarterly at best and (ii) published with lags of up to three quarters. These issues, related to the publication of BoP data, coupled with the volatility of portfolio investment, could hamper the prevention of some turmoil especially in EMs exchange rates and equity markets. Therefore, many proxies appeared in the academic literature, to approximate net capital flows (Calvo *et al.*, 2004 and 2008; Reinhart and Reinhart, 2009) and gross portfolio capital flows[1] (Miao and Pant, 2012), *e.g.*, changes in foreign exchange reserves, capital tracker, coincident indicator, etc.

In light of recent developments and concerns, we want to better understand foreign investors' sentiment measured by gross portfolio capital flows. Additionally, we are also looking for an indicator which can deal with and even circumvent BoP data weaknesses. To this end, we extend the framework of Miao and Pant (2012) who propose a composite coincident indicator for the liability side of BoP portfolio capital flows. This indicator is coincident in that it provides more frequent up-to-date information on cross-country portfolio flows using another database which are available three to nine months earlier than BoP data, namely the Emerging Portfolio Fund Research (EPFR) Global database. Among other things, EPFR provides weekly and monthly data on bond and equity flows for both DMs and EMs. Regarding the literature, there are very few papers that use the EPFR database. However, some of the largest international financial institutions such as the World Bank, the Bank of International Settlements, the IMF, the Organisation for Economic Co-operation and Development and some major central banks have been using EPFR data for many years. Yet, there are two papers[2] that are getting our attention. First, Jotikasthira *et al.* (2009) show a close correlation between EPFR data and portfolio flows stemming from BoP data. Second, Miao and Pant (2012) use this database and some control variables to estimate the BoP gross portfolio flows for EM regional aggregates.

In an error correction framework, we analyse the links between EPFR country flows and BoP gross portfolio flows. The idea is to build a new simple coincident indicator for BoP gross portfolio flows both for EM regional aggregates and EMs themselves. The paper first analyses the monthly EPFR country flows, and then compares, in a linear framework, these flows with the weekly country flows to better capture the short- term dynamics of foreign investors' sentiment. Even though EPFR data represent a sample of total flows, our indicator outperforms a simple linear rescale of EPFR data in approximating the liability side of BoP

[1] Gross portfolio capital flows refer to changes in portfolio liabilities of residents to non-residents. In other words, these are net purchases of non-residents in the relevant country.

[2] To our knowledge, we can mention Jotikasthira *et al.* (2009), Fratzschzer (2012), Forbes *et al.* (2012), Raddatz and Schmukler (2012), Fratzscher *et al.* (2012), Lo Duca (2012), Miao and Pant (2012). Each of these papers addresses very different topics.

portfolio capital flows. According to some robustness checks, our simple coincident indicator is relevant and accurate for regional aggregates as well as for large EMs. As a result, the EPFR based indicator is a suit- able candidate for practitioners who would like to have a simple and coincident proxy for gross portfolio capital flows. Furthermore, the construction of Investor Sentiment indices give us some relevant information on EMs asset returns. Lastly, EPFR data can be studied with much more granularity, *e.g.*, origin of flows, type of fund, sector allocations, type of investor, currency, etc., and could therefore be very useful both for policy makers and asset managers.

The paper is organised as follows: Section 2 introduces the data and presents in detail the emerging countries falling within the scope of our study. Section 3 aims at establishing the links between BoP portfolio investment and EPFR flows. We then outline how we build our simple coincident indicator. Section 4 presents empirical findings and robustness checks. We expose how this proxy could be practically used in Section 5. We conclude our findings in Section 6.

2. Data

The idea is to extract from the EPFR database, which contains fund flows, sector flows and country flows, the information usually taken from BoP portfolio investment[3]. We use quarterly and monthly data for BoP and EPFR flows respectively. Our sample consists of 29 major EMs[4] which have continuous quarterly BoP data coverage from the first quarter of 2005 to the third quarter of 2013. The 29 EMs in our sample represent the All EMs aggregate and are divided in four regional aggregates: eight in Emerging Asia, seven in Latin America, eleven in Emerging Europe, and three in Other EMs[5].

[3] We indifferently use different names for the same data: BoP portfolio investment, BoP portfolio capital flows, BoP capital flows, BoP flows, etc.

[4] Actually, our sample is a subsample of the 48 EMs covered in the IMF (2011a) capital flows policy paper. Initially, we removed the EMs with a very low weight compared to others. By doing this, we reduced the sample to 33 EMs. Furthermore, four EMs are excluded for data reasons: Malaysia, Morocco, Tunisia and Vietnam (*cf.* Appendix 1 for more details on the data availability).

[5] Emerging Asia includes China, India, Indonesia, Korea, Pakistan, Philippines, Sri Lanka and Thailand; Latin America includes Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela; Emerging Europe includes Bulgaria, Croatia, Czech Republic, Hungary, Kazakhstan, Lithuania, Poland, Romania, Russia, Turkey and Ukraine; Other EMs include Israel, Lebanon and South Africa.

2.1. BoP portfolio capital flows

According to the sixth edition of the Balance of Payments and International Investment Position Manual[6] (IMF, 2010), BoP portfolio investment:

(i) is defined as cross-border transactions and positions involving debt or equity securities, other than those included in direct investment or reserve assets;

(ii) covers, but is not limited to, securities traded on organised or other financial markets;

(iii) usually involves financial infrastructure, such as a suitable legal, regulatory, and settlement framework, along with market-making dealers, and a sufficient volume of buyers and sellers;

(iv) is characterised by the nature of the funds raised, the largely anonymous relationship between the issuers and holders, and the degree of trading liquidity in the instruments.

These portfolio investments belong either to residents of a considered country, *i.e.*, foreign assets of investors in this country, or to non-residents, *i.e.*, liabilities of this country to foreign investors. Transactions are positive if they represent a capital inflow in this country and negative otherwise (if they represent an outflow of capital from this country). Therefore, to better capture the gross cross-country portfolio flows, we focus only on the liability side of the BoP portfolio capital flows.

In this paper, we use quarterly consolidated BoP flows from BPM6. BoP bond and equity portfolio flows are available from Q1 2005 to Q4 2013 with a lag of one to three quarter(s) at best and for a limited number of EMs. Some countries such as Malaysia, Morocco and Vietnam do not have sufficient historical data to estimate a sustainable long-term relationship. In addition, Tunisia has been disregarded since the data are at best annual frequency statistics (*cf.* Appendix 1 for more details on data availability).

2.2. EPFR Global database

Emerging Portfolio Fund Research Global provides daily, weekly and monthly information about fund flows and asset allocations to build country flows and sector flows. EPFR covers

[6] Hereafter, we refer to this handbook with the conventional acronym BPM6.

104 developed and emerging countries for equity funds and 108 countries for the bond flows database. Here are some aspects to consider when using EPFR data:

(i) Funds flows are net flows, *i.e.*, the investor contribution/redemption into the fund. These flows exclude portfolios' performance and currency fluctuations;

(ii) Asset allocation data tracks the country (sector) weights in the provided EPFR funds flows;

(iii) Country (sector) net flows are supposed to estimate the capital flows into and out of the EMs in question.

Table 1. Bond and equity funds: EPFR database coverage

Note: The table provides a snapshot of the funds covered by EPFR on a monthly basis as of April 2014. The funds are split into two broad asset classes: bond and equity funds. Within these asset classes, funds are classified according to the type and the domiciliation of treated financial products. EPFR equity flows (USD 13,086 billion) are more represented than bond flows (USD 10,364 billion). Funds invested by the United States represent more than 40% of EPFR flows.

Fund Group	Number of Funds	Asset under Management (in USD billion)
Bond and Equity Funds	**56,599**	**23,450.11**
Bond Funds	**22,181**	**10,364.06**
Money Market	2,679	3,798.72
United States	5,271	2,699.35
Global	6,210	1,508.37
Balanced	2,436	1,387.91
High Yield	2,492	654.11
EMs	3,093	315.60
Equity Funds	**34,418**	**13,086.05**
United States	11,181	7,026.61
Global	9,826	3,533.27
Western Europe	5,233	1,195.71
Global EMs	2,297	551.41
Asia ex-Japan	2,948	381.53
Japan	1,115	220.05
Pacific	469	80.88
Latin America	533	44.00
EMEA[7]	816	52.59

[7] Europe, the Middle East and Africa.

Table 1 provides a snapshot of the funds covered by EPFR. The funds are split into two broad asset classes: bond and equity funds. Within these asset classes, funds are classified according to the type and the domiciliation of treated financial products. The first glance at Table 1 shows that the EPFR bond and equity flows each represent more than USD 10,000 billion but with a substantially different number of funds. In addition, the over-representation of funds invested by the United States is already obvious.

In this paper, we only consider country flows. In this purpose, data are collected on a monthly basis directly from asset managers through EPFR. The provided flows come mainly from several major market jurisdictions and offshore domiciles including Australia, Austria, Canada, Channel Islands, France, Germany, Hong Kong SAR, Luxembourg, Switzerland, United Kingdom, United States and others. Furthermore, approximately half of total flows collected by EPFR come from the United States with a pronounced dichotomy between equity assets and bond securities. Some gross flows are collected from large EMs such as Korea, Indonesia, Brazil, Russia, etc.; but they represent only a tiny share of total flows. Thus, we can consider, without loss of generality, that the flows collected by EPFR are gross flows, only for EMs, because these flows mainly come from DMs and some tax havens.

In the EPFR database, the equity flows generally start in January 2000 and continue to December 2013. In the same way, bond flows begin in January 2004. In case of missing data for a period not exceeding three months, they are replaced by zero. When the same problem occurs over a longer period, the country's asset class is removed from the study. Because of missing data, we expect some significant differences between EPFR and BoP flows for some periods and for some regions. For comparison to the BoP capital flows purposes, the monthly flows are aggregated to obtain quarterly flows, which are the same frequency as the BoP capital flows. Moreover, we cumulate BoP and EPFR quarterly flows over four quarters to smooth the series and have a better idea of the trend of portfolio flows towards EMs, *i.e.*, a proxy of foreign investors' sentiment.

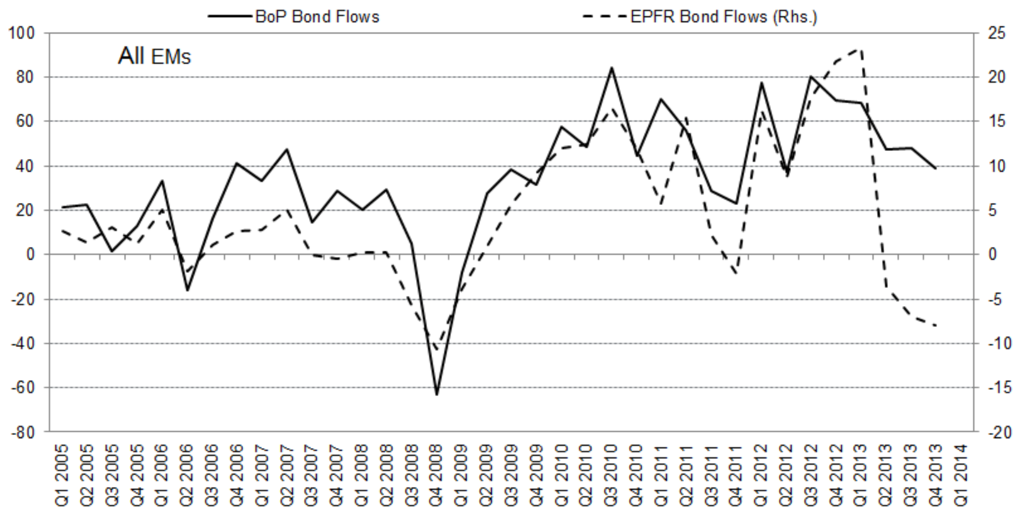
3. A simple coincident indicator for gross portfolio capital flows

Using the EPFR database presented above, we propose a coincident and up-to-date indicator for BoP portfolio investment liabilities. This indicator is coincident in that it happens in tandem with BoP gross portfolio flows. In addition, the indicator is up- to-date in that it provides more frequent and updated information on cross-country portfolio flows. Here, the aim is to estimate quarterly BoP bond and equity flows with data collected on EPFR which is more precisely country bond and equity monthly flows.

3.1. The coincidence between BoP and EPFR flows

Figure 1. Comparison of BoP and EPFR flows (USD billion)

Note: The figures plot the BoP portfolio capital flows (continuous line) and the EPFR country flows (dashed line). The upper graph concerns bond flows while the lower graph focuses on equity flows. As expected, the magnitude of EPFR flows is much smaller than BoP flows. More precisely, over the full sample period, the average share of EPFR capital flows in the gross BoP flows is 59% of BoP equity flows and 28% of BoP bond flows.



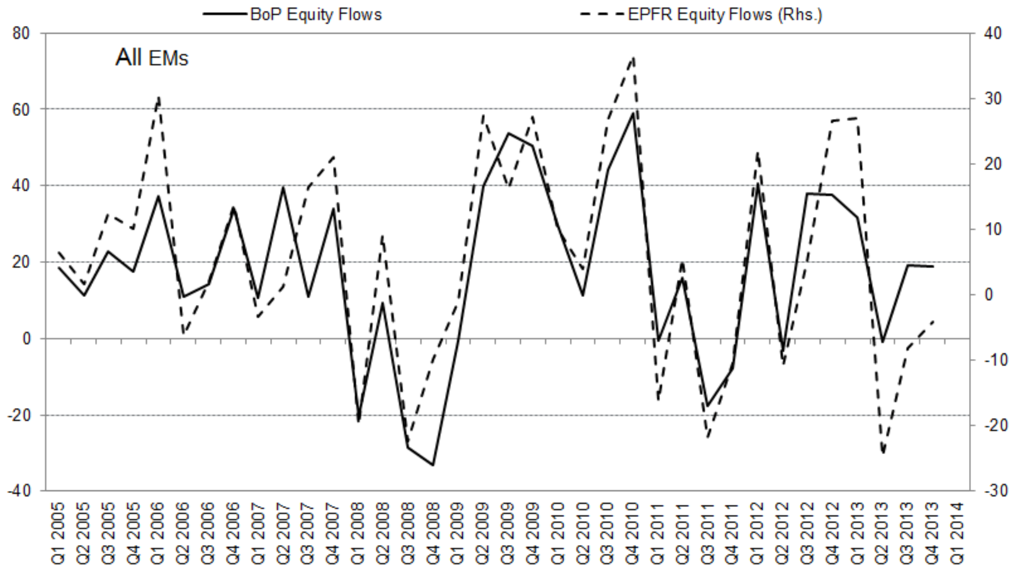


Figure 1 shows a comparison between EPFR and gross BoP portfolio capital flows. As expected, the magnitude of EPFR flows is much smaller than BoP flows. More precisely, over the full sample period, the average share of EPFR capital flows in the gross BoP flows is 59% of BoP equity flows and 28% of BoP bond flows. Furthermore, EPFR data seem to be a coincident indicator of gross BoP portfolio capital flows for most time periods. For instance, the relative decorrelation between BoP and EPFR portfolio flows during the pre-crisis period is mainly due to some mismatches between BoP and EPFR flows in Latin America. Table 2 provides information on the correlation between our two sources of portfolio flows for the All EMs aggregate for the full sample period and for the two sub-periods highlighted in Table 2, *i.e.*, Q1 2005 to Q3 2008 and Q4 2008 to Q3 2013 (*cf.* Appendix 2 for more details on the correlations between BoP and EPFR flows for each regional aggregate).

Table 2. Correlations between BoP and EPFR flows for All EMs

Note: The table shows that EPFR country flows tend to become increasingly correlated with BoP portfolio flows. This has been particularly true since the recent global financial crisis. Indeed, regarding the bond flows, the correlation increased from 60.6% before the crisis to 75.6% afterwards. However, the correlation between BoP and EPFR equity flows remains quite stable over the full sample period. We explain this by the fact that, over the full sample period, the average share of EPFR equity flows is more than a half of BoP equity flows, reflecting the long-term trend in correlation over time.

All EMs	Bond Flows	Equity Flows
Full Sample	**77.4%**	**85.3%**
Q1 2005 to Q3 2008	60.6%	82.0%
Q4 2008 to Q3 2013	75.6%	86.8%

3.2. Methodology

We consider the four-quarter moving sum of gross BoP and EPFR quarterly flows for bonds and equities. Over the entire sample period, *i.e.*, Q1 2005 to Q3 2013, BoP flows as EPFR flows are very volatile but the recent global financial crisis appears to present a break in these series. Thus, we start by testing the stationarity of the liability side of the BoP portfolio bond and equity flows as the gross bond and equity flows from EPFR with

Augmented Dickey-Fuller (1981, ADF hereafter) and Phillips-Perron (1987 and 1988, PP hereafter) unit root tests[8]. In Table 3, we present the unit root tests results for regional aggregates and some large EMs in each of them. For more detailed results, especially in smaller EMs, *cf.* Appendix 3. Table 3 shows that in more than two thirds of cases, the series that we study are integrated of the same order, namely the order one. Thus, it is highly likely that these series are cointegrated. In a more detailed way, Table 3 brings us two lessons:

(i) Overall, the larger the regional aggregates or EMs, the more BoP and EPFR flows have a propensity to have a common unit root;

(ii) Regarding the integration orders, there is a dichotomy between bond and equity flows. Indeed, bond flows have a higher propensity to have a unit root, while equity flows are more likely to be stationary in level.

Table 3. Unit root tests results (ADF and PP) for BoP and EPFR flows

Note: The table presents the ADF (PP) t-statistics. The figures in bold reflect the ADF (PP) t-statistics in level. *, **, *** denote rejecting the null hypothesis that there is a unit root at the 10%, 5% and 1% level of confidence, respectively. We show that in more than two thirds of cases, the series that we study are integrated of the same order, *i.e.*, $I\ (1)$.

Variable Area/Country	BoP Bond	EPFR Bond	BoP Equity	EPFR Equity
All EMs	-2.75*** (-2.79***)	-4,34*** (-3.17***)	-3.71*** (-3.79***)	**-2.36**** (-4.25***)
Emerging Asia	**-5.10***** (-2.68***)	-5.36*** (-2.84***)	**-2.76***** (-3.66***)	**-2.00**** (-4.09***)
China	-4.45*** (-4.66***)	**-5.19***** (-0.92)	-5.53*** (-4.54***)	**-4.12***** (-5.51***)
Indonesia	-4.52*** (-4.53***)	-5.30*** (-3.05**)	-3.26*** (-6.44***)	-5.57*** (-5.57***)
Latin America	-3.04*** (-3.11***)	-4.11*** (-3.34***)	-3.77*** (-3.77***)	-4.46*** (-4.46***)
Brazil	-5.44*** (-3.86***)	-4.37*** (-3.22***)	-3.51*** (-3.51***)	-4.53*** (-4.54***)
Emerging Europe	-3.49*** (-3.49***)	-3.91*** (-3.00***)	**-2.85***** **(-2.02**)**	**-3.01***** **(-2.02**)**

[8] The use of several tests to conclude on the nature of stationarity of the studied variables is essential to disambiguate on some test results. Indeed, the PP unit root tests differ from the ADF tests mainly in how they deal with serial correlation and heteroskedasticity in the errors. In particular, where the ADF tests use a parametric autoregression to approximate the ARMA structure of the errors in the test regression, the PP tests ignore any serial correlation in the test regression.

Turkey	-3.70*** (-3.70***)	-4.09*** (-2.87***)	-5.40*** (-4.80***)	**-2.26**** (-4.11***)
Other EMs	**-7.01***** (-4.02***)	-4.02*** (-3.79***)	**-2.52**** (-4.38***)	-4.14*** (-4.15***)
South Africa	**-4.05**** (-6.21***)	-1.68* (-3.91***)	**-2.20**** (-3.45***)	-4.49*** (-4.49***)

Table 4. Cointegration tests results (ADF and PP unit root tests on estimated residuals)

Note: The table presents the ADF (PP) t-statistics on the estimated residuals $\epsilon_{it} = Y_{it} - \hat{\beta}_i X_{it} - [\hat{\alpha}_i]$ where i denotes the different countries and regional aggregates, t denotes time, ϵ is the error term from OLS regressions of BoP gross portfolio capital flows, Y , on EPFR flows, X , $\hat{\beta}$ is the estimated cointegrating coefficient and $\hat{\alpha}$ is the estimated intercept (only if it is statistically significant). The figures in bold reflect the ADF (PP) t-statistics on the estimated residuals in level. *, **, *** denote rejecting the null hypothesis that there is a unit root at the 10%, 5% and 1% level of confidence, respectively. OLS denotes the fact that we estimate the OLS regression $Y_{it} = [\alpha_i] + \beta_i X_{it} + \varepsilon_{it}$. In this case, we don't need to test the stationarity of the estimated residuals. We see that more than 70% of the series are cointegrated, almost 15% are estimated in a simple OLS framework while about 15% are not considered because the variables are not integrated of the same order or because there is no cointegration relationship. At this point, it is interesting to note that the series which are not considered are mainly equity flows, more specifically toward small EMs. In fact, it is difficult to establish a cointegration relationship (or at least a simple linear relationship) when BoP flows are low and therefore EPFR flows (which are a sample of total flows) are even lower for the smaller EMs of the study. For more detailed results, especially for the smaller EMs, *cf.* Appendices 3 and 4.

Variable **Area/Country**	ϵ_{it}^{Bond}	ϵ_{it}^{Equity}
All EMs	-3.14*** (-1.94*)	-1.95* (-1.95*)
Emerging Asia	-5.10*** (-2.27**)	-2.49** (-1.72*)
China	OLS	-2.14** (-2.27**)
Indonesia	-2.91*** (-2.81**)	-2.71*** (-2.66***)
Latin America	-4.67*** (-2.01**)	-2.10** (-1.93*)
Brazil	-4.67*** (-1.87*)	-2.25** (-1.74*)
Emerging Europe	-2.45** (-2.61**)	OLS
Turkey	-3.80*** (-2.53**)	-2.07** (-2.33**)
Other EMs	-3.06*** (-2.09**)	-4.68*** (-4.68***)
South Africa	-2.10** (-3.11***)	-5.01*** (-5.11***)

To find out whether the series are cointegrated and as we are studying the cointegration with only one explanatory variable, we use the ADF and PP unit root tests again but on the estimated residuals[9] from Ordinary Least Squares (OLS) regressions of BoP gross bond and equity flows over EPFR flows. We provide the cointegration tests results in Table 4. As we expected, the series have a high propensity to be cointegrated because of the concomitant nature of BoP and EPFR flows. For more detailed results, especially for the smaller EMs, *cf.* Appendices 3 and 4.

When BoP and EPFR portfolio flows are cointegrated, we estimate an Error Correction Model (ECM) to capture both the long-term relationship and the short-term dynamics between our two sources of portfolio capital flows. The ECM is defined as follows:

$$\Delta Y_{it} = \gamma_i \Delta X_{it} + \delta_i \epsilon_{it-1} + \nu_{it} \tag{1}$$

where i denotes the different countries and regional aggregates, t denotes time, Y denotes the BoP gross portfolio capital flows, X denotes the EPFR flows, ϵ is the estimated residuals from the OLS regressions of Y on X and ν is the error term. According to the Granger representation theorem (Engle and Granger, 1987), the error correction model includes variables in level and in variation. The use of the error correction model in the case of cointegration provides more reliable forecasts than if we only used the long- term relationship. Indeed, in a simple OLS framework which represents the long-term relationship, the estimated results are distorted by the non-stationarity of the series. In the OLS regressions $Y_{it} = [\alpha_i] + \beta_i X_{it} + \varepsilon_{it}$, we expect that BoP gross portfolio capital flows are positively associated with EPFR flows, *i.e.*, $\beta > 0$. In the ECM regressions in (1), we expect that an increase in BoP gross portfolio capital flows is associated with an increase in EPFR flows, *i.e.*, $\gamma > 0$. In addition, a long-run relationship exists between BoP gross portfolio capital flows and EPFR flows only if δ, which measures the speed of adjustment of the endogenous variable towards the equilibrium, is significantly negative.

[9] Considering that the relationship is on the estimated residuals and not on the "real" ones, we cannot refer to the usual Dickey-Fuller tables to conduct unit root tests. We have to look at the MacKinnon tables (MacKinnon, 1996).

4. A powerful coincident indicator

A powerful coincident indicator is an indicator which occurs almost exactly at the same time as the conditions they signify. In our case, the EPFR based indicator may explain well the trend in investors' sentiment as measured by the dynamic of quarterly BoP gross portfolio flows. However, there is a real dichotomy between bond and equity markets. Indeed, since the global financial crisis, we notice a diversification trend towards bond markets while this diversification in equity markets occurred earlier. Some robustness checks are also presented in this section. Estimates for small EMs[10] are discussed at the end of this section.

4.1. An up-to-date analysis for gross portfolio capital flows

We are using a two-step procedure. We provide the estimates for regional aggregates as a first step and we construct the EPFR based coincident indicator for the liability side of BoP portfolio capital flows as a second step.

Tables 5 and 6 summarise the regression results for portfolio bond and equity flows respectively. In Figures 2 and 3, we provide the evolution of our simple coincident indicator for bond and equity flows, respectively. In almost all cases, the simple coincident EPFR based indicator is powerful in approximating gross BoP bond and equity portfolio flows. The fact that our models fit quite well shows that our indicator is quite accurate. Indeed, the R^2 is about 0.56[11] on average and oscillates between 0.32 and 0.66 for bond flows and between 0.59 and 0.83 for equity flows. Note that the estimates for the larger aggregate, *i.e.*, All EMs, are the most accurate both for bond and equity flows because aggregated data for All EMs are available over the entire sample and with high variance, both for BoP and EPFR portfolio capital flows.

[10] Because of space limitation, the estimated results for small EMs are not reported but available upon request.
[11] The average R^2 takes into account only the estimates with significantly negative cointegrating coefficients.

Table 5. A coincident indicator for BoP portfolio bond flows

Note: The table presents the results of the ECM $\Delta Y_{it} = \gamma_i \Delta X_{it} + \delta_i \epsilon_{it-1} + \nu_{it}$ and the coefficient β of the OLS $Y_{it} = [\alpha_i] + \beta_i X_{it} + \varepsilon_{it}$. Standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level of confidence, respectively. We want to emphasize that δ should be significantly negative. Otherwise, the ECM regression is not valid. Moreover, δ measures the speed at which prior deviations from equilibrium are corrected. Finally, if $X \rightsquigarrow I(d1)$ and $Y \rightsquigarrow I(d2)$ (with $d1 \neq d2$ and $d_j \in \mathbb{Z}^+$ for $j = \{1,2\}$), then we do not estimate any model to avoid spurious regression because the variables which are integrated of a different order cannot be cointegrated. The R^2 oscillates between 0.32 for the Emerging Asia aggregate and 0.66 for the All EMs aggregate. For more detailed results on the larger EMs, *cf.* Appendix 5.

Dependent Variable: *D(BoP Bond)*

Q1 2006 - Q3 2013

Area / Variable	All EMs	Emerging Asia	excluding South Korea	Latin America	Emerging Europe	Other EMs
γ_i	2.304*** *(.362)*	1.962** *(.734)*	2.119*** *(.379)*	1.536*** *(.416)*	3.239*** *(.471)*	3.792*** *(.937)*
δ_i	-0.398*** *(.142)*	-0.201* *(.110)*	-0.134* *(.072)*	-0.253** *(.110)*	-0.419** *(.153)*	-0.236** *(.107)*
Long-term relationship β_i	3.495*** *(.245)*	2.631*** *(.564)*	3.876*** *(.394)*	3.400*** *(.379)*	4.074*** *(.272)*	2.290*** *(.683)*
Number of Observations	31	31	31	31	31	31
Adj. R-Squared	0.66	0.32	0.52	0.36	0.63	0.37

Table 6. A coincident indicator for BoP portfolio equity flows

Note: The table presents the results of the ECM $\Delta Y_{it} = \gamma_i \Delta X_{it} + \delta_i \epsilon_{it-1} + \nu_{it}$ and the coefficient β of the OLS $Y_{it} = [\alpha_i] + \beta_i X_{it} + \varepsilon_{it}$. Standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level of confidence, respectively. For the simple OLS regression, estimates are made between Q4 2005 and Q4 2012. We want to emphasize that δ should be significantly negative. Otherwise, the ECM regression is not valid. Moreover, δ measures the speed at which prior deviations from equilibrium are corrected. Finally, if $X \rightsquigarrow I(d1)$ and $Y \rightsquigarrow I(d2)$ (with $d1 \neq d2$ and $d_j \in \mathbb{Z}^+$ for $j = \{1,2\}$), then we do not estimate any model to avoid spurious regression because the variables which are integrated of a different order cannot be cointegrated. The R^2 oscillates between 0.59 for the Emerging Asia excluding South Korea and 0.83 for the All EMs aggregate. For more detailed results on the larger EMs, *cf.* Appendix 5.

Dependent Variable: ***D(BoP Equity)***

Q1 2006 - Q3 2013

Area / Variable	All EMs	Emerging Asia	excluding South Korea	Latin America	Emerging Europe	Other EMs
γ_i	1.381***	1.426***	1.039***	0.996***		2.114***
	(.115)	*(.174)*	*(.176)*	*(.176)*		*(.401)*
δ_i	-0.287**	-0.314**	-0.267**	-0.268**		-0.063
	(.125)	*(.136)*	*(.120)*	*(.122)*		*(.062)*
Long-term relationship						
β_i	1.644***	1.835***	1.271***	1.238***	0.952***	1.117*
	(.128)	*(.179)*	*(.222)*	*(.214)*	*(.247)*	*(.802)*
Number of Observations	31	31	31	31	32	31
Adj. R-Squared	0.83	0.69	0.59	0.61	0.32	0.48

In all cases, an increase in the EPFR country flows is positively and significantly associated with an increase of BoP portfolio flows. Moreover, for All EMs, the response of BoP bond flows to an increase of one dollar in EPFR bond flows is around 2.3 dollars, while it is only around 1.4 dollars for equity flows. Besides, funds invested on equity markets are more represented in the EPFR database than funds invested in bond markets and thus this is the most important bias of the EPFR database. From a more statistical point of view, the coefficient δ always shows the expected sign. However, δ is not always significant as we can see in the case of Other EMs aggregate.

If we take a closer look at Emerging Asia, we note that South Korea may bias this regional aggregate. According to the classification criteria, South Korea is a country which is sometimes considered as an EM and sometimes as a DM. In this case, the consideration we have made on the gross nature of EPFR flows no longer holds. Indeed, South Korean residents invest significantly abroad and EPFR data reflect this fact quite faithfully[12]. Furthermore, if we estimate the BoP gross bond flows for Emerging Asia removing South Korea, the coefficient δ remains significantly negative and the R^2 climbs from 0.32 to 0.52. However, if we do the same for BoP gross equity flows, δ remains significantly negative but the explanatory power of the regression decreases from 0.69 to 0.59. We explain this by the

[12] EPFR reports that, on average, more than 35% of gross equity flows are invested abroad and this share is about 15% for gross bond flows.

fact that, taken country by country, ECM estimates for gross equity flows in Emerging Asia are spurious in the case of India, Pakistan and Philippines, *i.e.*, the variables are integrated of a different order and cannot be cointegrated or the coefficient δ is not significant.

From an economic standpoint, we can identify three highlights from Figures 2 and 3:

(i) The dynamics of BoP gross portfolio capital flows in each regional aggregate and, to a lesser extent, in large EMs, broadly follow the same path because these BoP flows follow a common story. Indeed, according to the IMF terminology (2011a), we identify three global waves[13] of capital inflows in the time interval we consider in this paper: Q4 2006 to Q2 2008, Q3 2009 to Q4 2010 and Q1 2012 to Q1 2013.

(ii) The analysis slightly differs depending on the asset class we consider. In fact, the appetite for EM assets began in the 1990s and initially concerned the equity markets which were deeper and more liquid than bond markets, which were barely existed at that time. In the 2000s, the emerging bond markets expanded greatly and investors tended to diversify their portfolios. This led to the first wave of capital inflows we are considering, *i.e.*, Q4 2006 to Q2 2008. The second and third waves of inflows have been more a matter of search for yield after the global financial crisis and the attractiveness for emerging bond markets continued to strengthen during these periods.

(iii) During the second wave of capital inflows, the search for yield has not been without selectivity. Indeed, in terms of dynamics and amounts, on the emerging equity markets, Latin America and Emerging Asia were preferred to Emerging Europe and Other EMs while on the emerging bond markets, Latin America and Emerging Europe were preferred to Emerging Asia and Other EMs.

[13] In the IMF terminology (2011a), surges, episodes and waves are defined: (i) a surge refers to a quarter or a year during which gross inflows significantly exceed their long-run trend and are also large in absolute magnitude; (ii) an episode of capital inflows refers to a prolonged surge and (iii) a wave of capital inflows refers to a large number of country episodes occurring at the same time.

Figure 2. BoP bond flows (four-quarter moving sum) and EPFR coincident indicator (USD billion)

Note: The figures plot the four-quarter moving sum of BoP portfolio bond flows (continuous line) and the EPFR coincident indicator for bond flows (dashed line). Each figure reflects a different regional aggregate. According to the IMF terminology (2011a), we identify three global waves of capital inflows in the time interval we consider in this paper: Q4 2006 to Q2 2008, Q3 2009 to Q4 2010 and Q1 2012 to Q1 2013. For more detailed results on the larger EMs, *cf.* Appendix 5.

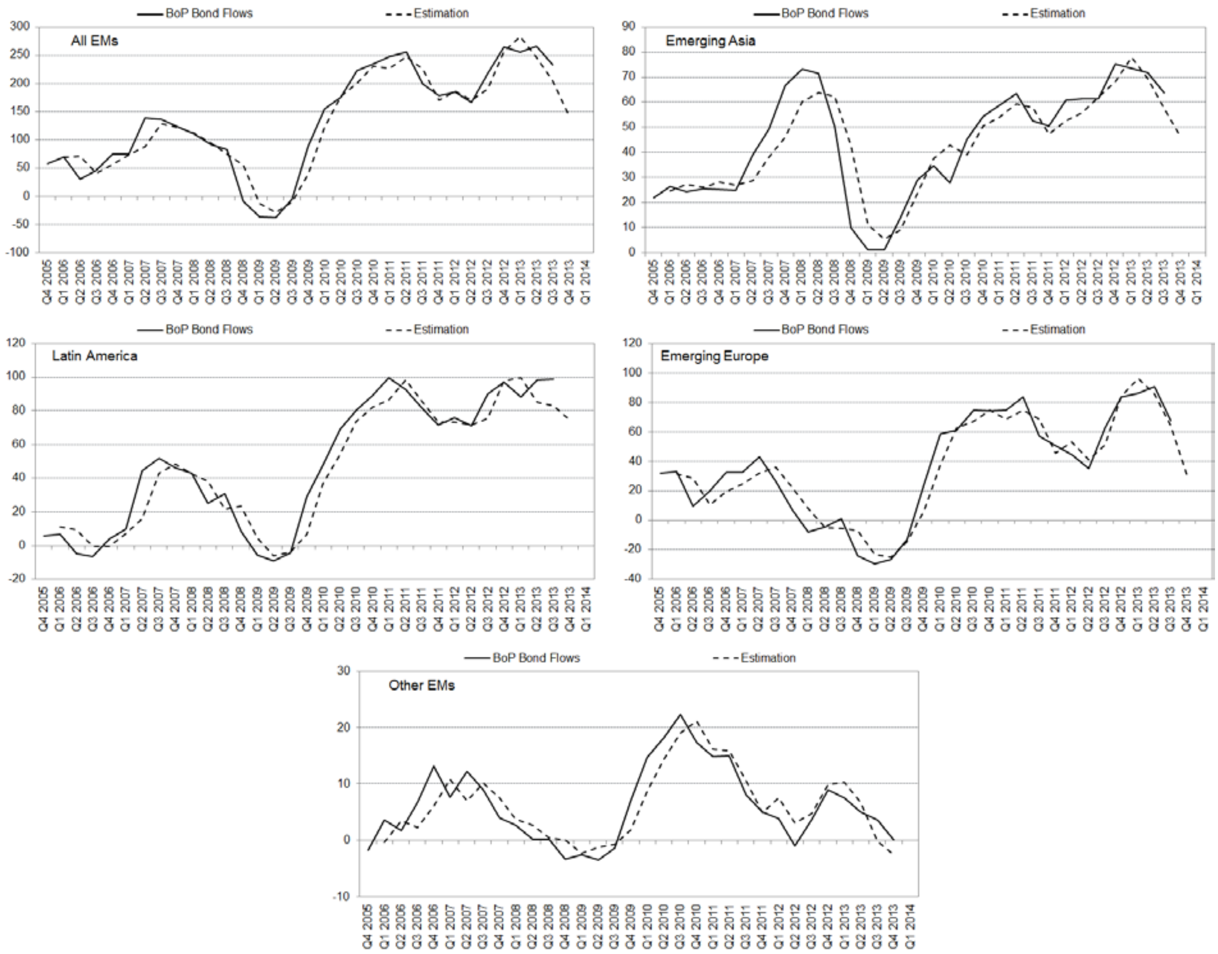
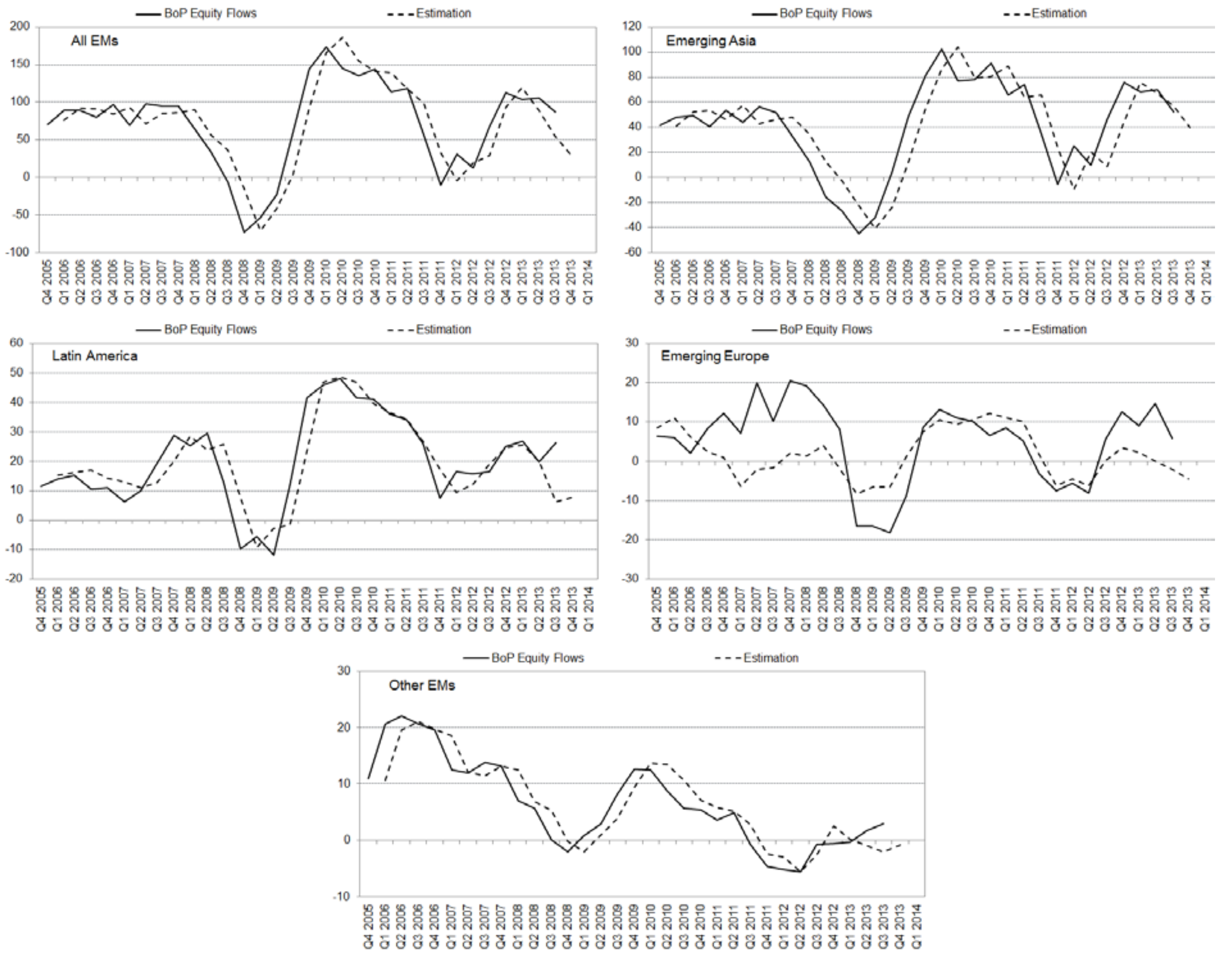


Figure 3. BoP equity flows (four-quarter moving sum) and EPFR coincident indicator (USD billion)

Note: The figures plot the four-quarter moving sum of BoP portfolio equity flows (continuous line) and the EPFR coincident indicator for equity flows (dashed line). Each figure reflects a different regional aggregate. According to the IMF terminology (2011a), we identify three global waves of capital inflows in the time interval we consider in this paper: Q4 2006 to Q2 2008, Q3 2009 to Q4 2010 and Q1 2012 to Q1 2013. For more detailed results on the larger EMs, *cf.* Appendix 5.



4.2. *Robustness checks: how good is our coincident indicator?*

We have shown that our coincident indicator was performing well in-sample but we must ensure that the regression results are robust and relevant making some out-of-sample forecasts and tracking error measurements.

4.2.1. *Out-of-sample forecasts*

Here, we perform some validity tests of our EPFR based coincident indicator. We want to know if it can help us to predict the magnitude of actual BoP gross portfolio capital flows in a real time framework. For this purpose, we estimate rolling regressions to generate one-quarter-ahead out-of-sample forecasts for BoP portfolio flows. We apply our simple coincident indicator in a real time setting between Q2 2010 and Q3 2013[14] when most EMs in our sample have experienced both surges and sudden stops in gross portfolio flows. We start by estimating our model up to Q1 2010 and compute their one-quarter-ahead forecast for BoP gross portfolio capital flows in Q2 2010. We perform this recursively by moving the estimation and forecast windows one quarter ahead to obtain the real time forecasts for each quarter between Q3 2010 and Q3 2013.

In Figure 4, we compare our simple coincident indicator with its one-period-ahead forecast for the All EMs aggregate. We can highlight three main conclusions from this application:

(i) Out-of-sample forecasts track almost perfectly with the EPFR based coincident indicator estimated over the full sample period. Indeed, the values of the coefficients for the one-period-ahead forecasts remain very close to those of the estimated coefficients on the whole sample. This first result attests to the robustness of the regression results;

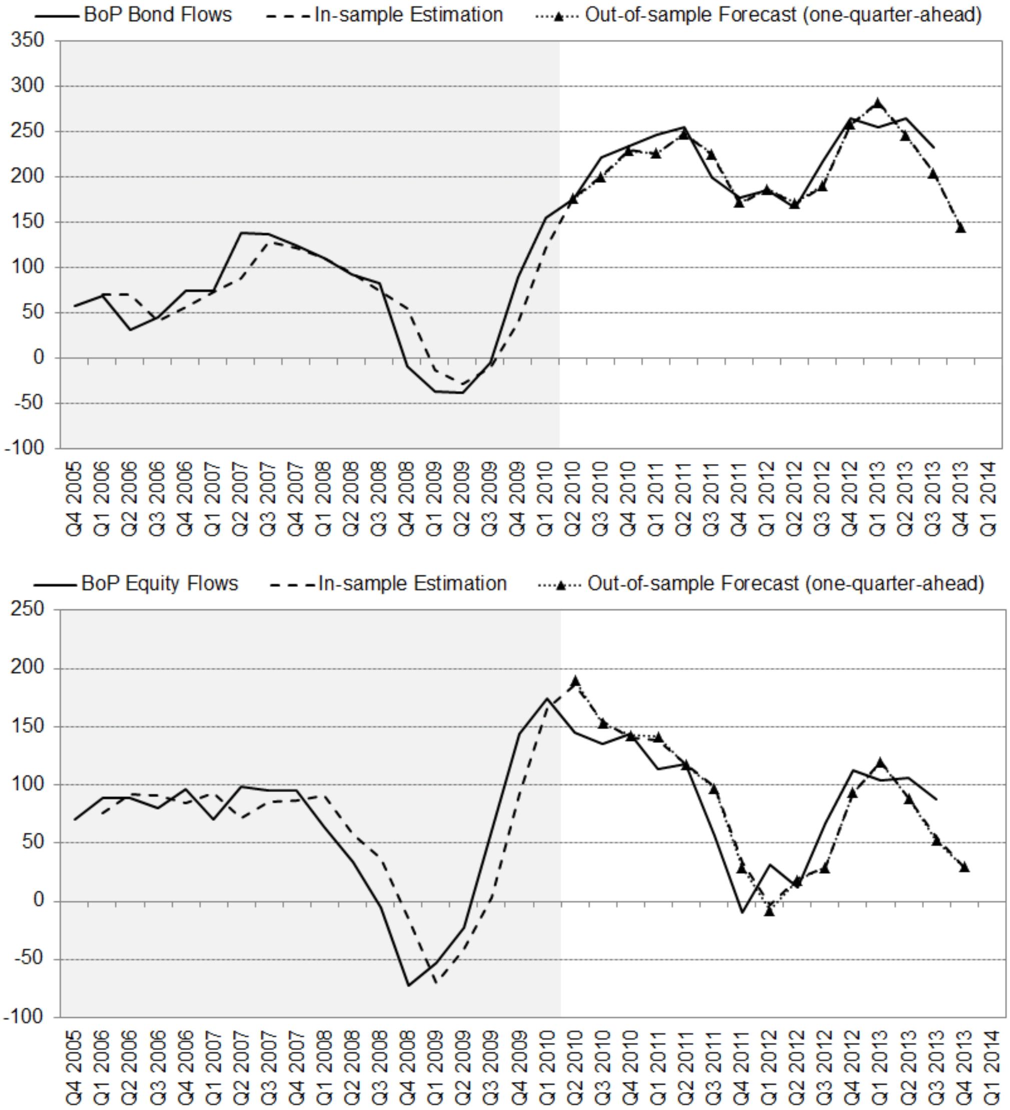
(ii) As for the simple coincident indicator derived over the full sample period, the one-quarter-ahead forecasts are closely aligned with the realised BoP gross portfolio capital flows that the IMF provides subsequently. This supports the relevance of our EPFR based coincident indicator and confers upon it an up-to-date capacity;

Based on the recent data available for the All EMs aggregate, our coincident and up-to-date EPFR based indicator projects a significant decrease of bond and equity flows toward EMs. Moreover, this decline is expected to stabilise in light of the latest data provided by EPFR.

[14] As we have seen before, estimates of BoP gross bond flows for China and estimates of BoP gross equity flows for Emerging Europe are conducted in an OLS framework. Therefore, both estimates and computations of out-of-sample forecasts begin in Q1 2010

Figure 4. One-period-ahead forecasts of the EPFR coincident indicator for All EMs (USD billion)

Note: The figures plot the four-quarter moving sum of BoP portfolio capital flows (continuous line), the in-sample estimation (dashed line) and the one-quarter-ahead out-of-sample forecast (dotted line with triangular markers). The shaded area corresponds to the in-sample period while the white area corresponds to the out-of-sample period. The upper graph concerns bond flows while the lower graph focuses on equity flows. Out-of-sample forecasts track almost perfectly with the EPFR based coincident indicator estimated over the full sample period. Furthermore, the one-quarter-ahead forecasts are closely aligned with the realized BoP gross portfolio capital flows that the IMF provides subsequently.



More broadly, the out-of-sample forecasts for other regional aggregates as for large EMs are very robust and allow us to draw the same conclusions as for the All EMs aggregate.

4.2.2. Tracking error measurements

In order to get a more precise idea of the forecast accuracy of our EPFR based co-incident indicator, we compute four tracking error measurements. The Mean Absolute Error (MAE) or the Root Mean Square Error (RMSE) which are among the most commonly used absolute tracking error measurements[15], the Median Absolute Percentage Error (MdAPE) and the Normalised Root Mean Square Error (NRMSE)[16].

Table 7. Tracking error measurements for our simple coincident indicator of gross portfolio flows

Note: Tracking error measurements are computed as follows: $MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{Y}_t - Y_t\right|$; $MdAPE = median\left\{\left|\frac{\hat{Y}_t - Y_t}{Y_t}\right|, t = 1, \dots, T\right\}$; $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{Y}_t - Y_t\right)^2}$ and $NRMSE = \frac{RMSE}{max(Y_t) - min(Y_t)}$. The RMSE is always greater than or equal to the MAE and if we take the example of the All EMs aggregate, we can say that, for bond flows, the MAE is around USD 21.3 billion when the standard error (RMSE) is around USD 25.9 billion. Regarding the scale-independent measurements, the larger the regional aggregates or the EMs, the smaller the MdAPE and the NRMSE. For the All EMs aggregate, we can see that the MdAPE and the NRMSE are smaller for bond flows than for equity flows (MdAPE: 12% vs. 29% and NRMSE: 8% vs. 12%) reflecting the relative higher accuracy of bond flows estimates.

Error Measurements	Bond				Equity			
Area/Country	MAE	MdAPE	RMSE	NRMSE	MAE	MdAPE	RMSE	NRMSE
All EMs	21.3	12%	25.9	8%	24.1	29%	28.7	12%
Emerging Asia	7.2	14%	9.6	13%	17.8	32%	20.8	14%
China	1.5	56%	1.9	6%	5.6	20%	7.3	18%
India	2.2	59%	3.2	18%	7.1	43%	8.4	16%
Indonesia	1.8	17%	2.5	15%	0.7	41%	0.8	18%
South Korea	5.9	15%	8.8	14%	7.6	52%	9.0	12%
Pakistan	0.2	50%	0.3	16%	0.2	53%	0.3	11%
Philippines	1.2	30%	1.6	13%	0.4	46%	0.4	14%
Thailand	0.8	24%	1.0	8%	1.3	37%	1.6	15%

[15] The use of absolute or squared values prevents negative and positive errors from offsetting each other but since these two metrics are scale-dependent, none of them are meaningful to compare multiple time series which have different scales.

[16] These two metrics, *i.e.*, the MdAPE and the NRMSE, both have the advantage of being scale-independent, so we can use them to compare forecast performance between different time series.

Error Measurements **Area/Country**	Bond				Equity			
	MAE	MdAPE	RMSE	NRMSE	MAE	MdAPE	RMSE	NRMSE
Latin America	8.2	15%	10.4	10%	564	19%	7.9	13%
Argentina	1.8	23%	2.5	15%	0.4	61%	0.5	23%
Brazil	5.0	34%	6.3	16%	5.0	30%	6.9	13%
Chile	1.2	33%	1.4	12%	0.6	24%	0.9	11%
Colombia	1.0	34%	1.2	12%	0.3	52%	0.4	11%
Mexico	3.9	16%	4.9	6%	2.1	64%	2.7	16%
Peru	0.3	22%	0.7	10%	0.1	59%	0.1	16%
Venezuela	1.3	45%	1.7	17%	8.7	15,879%	10.9	3,609%
Emerging Europe	8.4	18%	9.7	8%	7.7	84%	9.4	24%
Bulgaria	0.3	58%	0.4	15%	0.1	117%	0.1	16%
Croatia	0.6	53%	0.8	18%	0.2	83%	0.4	40%
Czech Republic	1.1	36%	1.5	15%	0.4	83%	0.4	21%
Hungary	2.1	39%	2.5	15%	0.7	86%	1.0	17%
Kazakhstan	1.8	44%	2.4	13%	0.7	110%	1.2	22%
Lithuania	0.5	46%	0.8	15%	0.1	103%	0.1	22%
Poland	2.6	29%	3.3	11%	0.9	38%	1.1	11%
Romania	1.1	59%	1.5	14%	0.1	65%	0.1	14%
Russia	2.2	28%	2.9	9%	4.2	70%	5.8	17%
Turkey	3.3	26%	4.3	9%	0.9	33%	1.1	15%
Ukraine	1.0	30%	1.3	11%	0.1	36%	0.2	8%
Other EMs	6.7	52%	8.2	19%	2.7	49%	3.5	13%
Israel	1.8	50%	2.5	13%	1.8	73%	2.2	23%
Lebanon	0.4	40%	0.6	15%	0.4	46%	0.5	29%
South Africa	2.5	50%	3.0	16%	2.5	50%	2.7	14%

(i) Overall, when the MdAPE are small (respectively high), the NRMSE are small (respectively high) too, reflecting the adequacy of these tracking error measures;

(ii) The larger the regional aggregates or the EMs, the smaller the MdAPE and the NRMSE, meaning that the larger the regional aggregates or the EMs, the more accurate the estimates;

(iii) The MdAPE and the NRMSE are smaller for bond flows than for equity flows. This emphasises that the estimates for bond flows are more accurate than for equity flows.

Broadly speaking, we can reasonably say that the simple and coincident EPFR based indicator we propose in this paper is very meaningful for regional aggregates and large EMs. In addition, the robustness checks support the accuracy of the regression results and the relevance of our EPFR based indicator. Furthermore, we have shown that estimates for bond flows are more accurate than for equity flows. However, one of the methodological limitation of this study is the relative lower accuracy of small EMs estimates. Indeed, the scale-independent tracking error measures for the smaller EMs of the sample are higher than those for the larger EMs. For instance, the equity flows estimates for Venezuela are the least relevant of our study. It is mainly due to the fact that there are few portfolio capital flows to those small EMs and even if there are some flows, EPFR provides them with a very low variance and, which makes the estimates of gross portfolio flows quite ineffective. Another reason is that both cyclical and structural pull factors, which typically refer to the relative attractiveness of the countries, are fewer and/or difficult to highlight for the smaller EMs in the sample, according to EPFR data only.

5. Applying the simple coincident indicator to gauge Investor Sentiment towards EMs

Conceptually, Investor Sentiment, also called Market Sentiment, may be defined as the aggregate attitude or appetite of the investment community at a given time toward a particular security or, in our case, toward a larger financial market. In other words, Investor Sentiment is the feeling or tone of a market as revealed through flows and/or price movements of the securities traded in that market. Brown and Cliff (2004) define Investor Sentiment as the excessive optimism or pessimism in a particular market while for Baker and Wurgler (2006), Investor Sentiment is the propensity to speculate. Here, we propose to measure Investor Sentiment towards EMs with our simple and coincident EPFR based indicator.

Box 1: Comparison of weekly and monthly EPFR country flows

The purpose of this Box is to compare the monthly EPFR country flows with the highest frequency of country flows available on EPFR, *i.e.*, the weekly frequency. Actually, the EPFR database coverage is somewhat different because there are fewer funds covered (and hence fewer flows) on a weekly basis than on a monthly basis. To this end, we aggregate the weekly data to obtain monthly data from January 2005 to September 2013. According to ADF and PP unit root tests, the series are stationary in level and, therefore, we estimate the following OLS:

$$Y_{it} = \beta_i X_{it} + \varepsilon_{it} \tag{2}$$

where i denotes the different countries and regional aggregates, t denotes time, Y denotes the monthly EPFR country flows, X denotes the monthly aggregate EPFR country flows and ε is the error term.

Appendix 6 presents the results of the OLS in (2). As we can see, weekly and monthly EPFR country flows are quite comparable. Indeed, the R^2 oscillates around 0.90 and the scale factor (represented by the coefficient β which is always significant) is fairly stable both for bond and equity flows. β varies between 1.4 and 1.6 for bond flows while it varies between 1.1 and 1.2 for equity flows. Overall, monthly bond flows represent about 1.5 times the monthly aggregate bond flows, whereas monthly equity flows represent about 1.15 times the monthly aggregate equity flows. Without loss of generality, it appears that the weekly EPFR country flows provide relevant information for practitioners who would like to approximate BoP gross portfolio capital flows in a real time framework. Moreover, the weekly EPFR country flows are available each week with only one week’s delay. Consequently, rolling the time window and applying the different scale factors gives us relevant and accurate estimates of monthly EPFR country flows with a higher frequency than the monthly EPFR country flows.

5.1. Investor Sentiment towards EMs

As mentioned above, Investor Sentiment may be measured through flows and/or price movements of the securities traded in a particular market. Obviously, in the case of our study, we focus on EPFR portfolio flows to develop some indices reflecting the investor appetite for EMs. Before building some Investor Sentiment indices based on weekly data, we want to ensure that weekly and monthly EPFR country flows are com- parable because EPFR database coverage is somewhat different on a weekly basis than on a monthly basis. We compare these two data frequencies in Box 1

Since weekly and monthly EPFR country flows are comparable, we provide a simple way to build Investor Sentiment indices towards the largest regional aggregate of this study, *i.e.*, the All EMs aggregate, for different types of assets. As a first step, we need to detrend the series to better capture the cyclical trend in investors' sentiment. In fact, the purpose is to remove the trend component of the time series which are the weekly EPFR country flows for bond, equity and the sum of bond and equity flows[17]. Knowing that the trend is not supposed to be linear, we decide to use a Hodrick-Prescott filter (Hodrick and Prescott, 1997) to remove this nonlinear trend. Given that we use weekly data, Hodrick and Prescott (1997) suggest using a smoothing parameter value of 270,400[18]. In a second step, to better compare each Investor Sentiment index, we compute a standard score (z-score) with learning effect. In other words, at each date t and for each EPFR detrended flow, we remove the average from t = 0 to t and we then divide by the standard deviation from t = 0 to t. The All EMs investor sentiments are reflected in Figure 5[19].

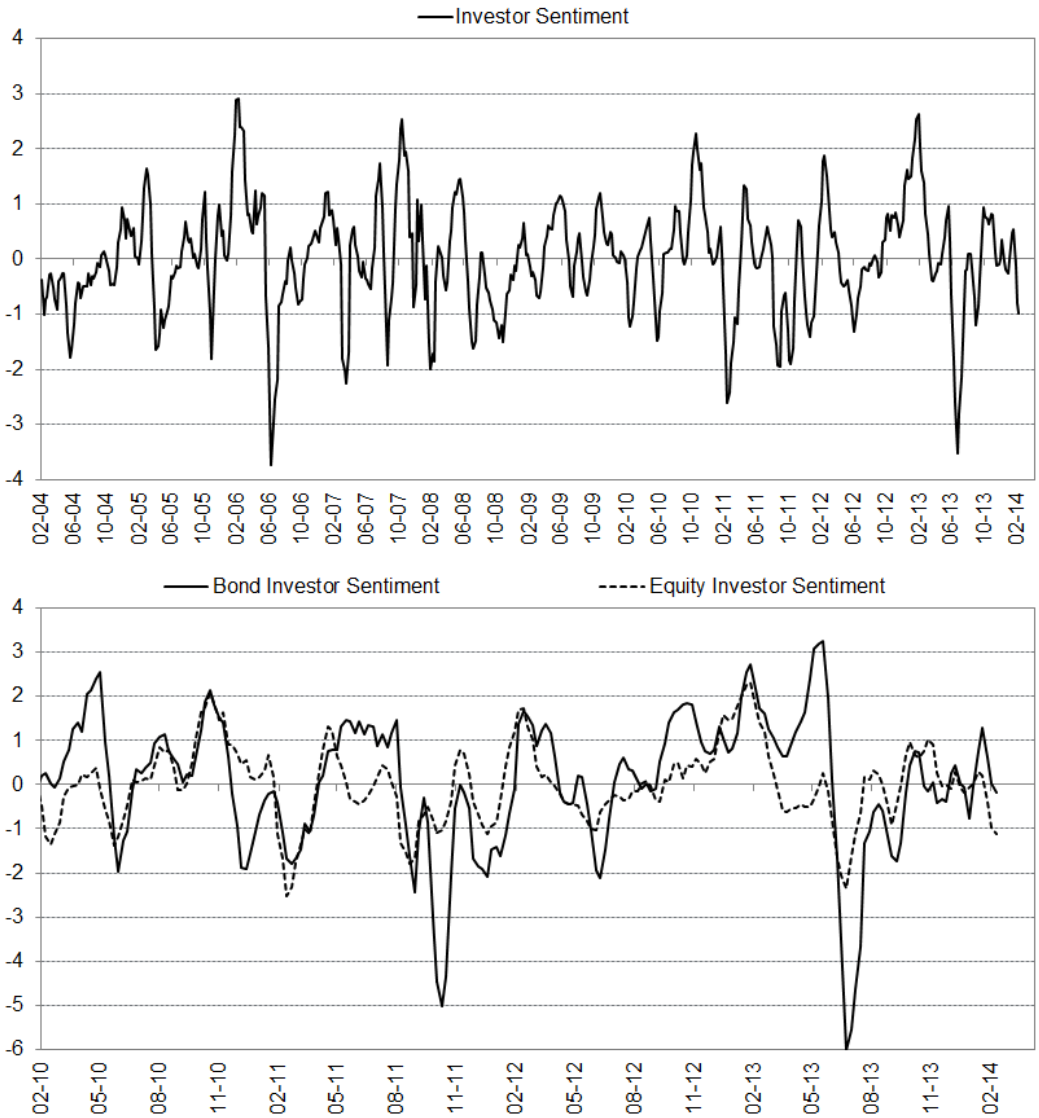
[17] The EPFR All EMs aggregate is composed of more than 90 EMs but the trend in this aggregate is virtually the same as our All EMs aggregate, which is composed of 27 major EMs.

[18] The value of the smoothing parameter λ is computed using the frequency power rule of Ravn and Uhlig (2002) which corresponds to the number of periods per year divided by 4 raised to a power value and multiplied by 1600. Although Ravn and Uhlig (2002) recommend using a power value of 4, we prefer to use a power value of 2, yielding the original Hodrick and Prescott (1997) values. Having said that, using a power value of 4 brings us to virtually similar results.

[19] For the sake of greater clarity and readability, the All EMs Investor Sentiment indices are smoothed using a four-week moving average. However, notably for the Granger non-causality tests (Granger, 1969), we use the unsmoothed Investor Sentiment indices to assess the coincident nature of our simple high frequency indicator.

Figure 5. All EMs Investor Sentiment indices (four-week moving average)

Note: The figures plot the four-week moving average of the All EMs Investor Sentiment indices. The upper graph concerns the sum of bond flows and equity flows for the All EMs aggregate while the lower graph focuses on each asset classes. If we focus on the All EMs Investor Sentiment index deteriorating below two standard deviations in the upper graph, we can describe four periods of heavy stress: (i) mid-2006, (ii) early 2007 to early 2008, (iii) early 2011 and (iv) mid-2013.



In the first chart of Figure 5, we can highlight several important events that have rocked EMs. Indeed, if we focus on All EMs Investor Sentiment index deteriorating below two standard deviations, we can describe four periods of heavy stress:

(i) Mid-2006: Rising inflation concerns and tightening by major central banks had a marked impact on financial markets between March and June. There was a more general retreat from equity markets and emerging market currencies in May and June.

(ii) Early 2007 to early 2008: This period has been characterised by many questions and concerns about the sustainability of the real estate market in the United States. In February 2007, HSBC, one of the world's largest banks, wrote down its holdings of subprime-related mortgage-backed securities by USD 10.5 billion. By April 2007, over 50 mortgage companies had declared bankruptcy. In July 2007, two Bear Stearns hedge funds collapsed.

(iii) Early 2011: Although the implementation of stimulus measures in 2009 had resulted in a rebound in economic activity in EMs in 2010, this economic activity slowed significantly in 2011. This slowdown was partly driven by economic factors, both internal (domestic demand particularly weak) and external (drop in exports due to a lower demand from DMs, end of the second wave of the Federal Reserve Quantitative Easing). In addition, structural factors had also played in this downturn. The potential growth of EMs had declined, particularly for China.

(iii) Mid-2013: May 22, 2013, the Federal Reserve publicly described conditions for scaling back and ultimately ending its highly accommodative monetary policy (better known as "Fed Tapering"). Some EMs subsequently experienced sharp reversals of capital inflows, resulting in sizable currency depreciation.

From a practical point of view, Investor Sentiment indices help us to better understand the investment dynamic towards EMs. Moreover, Investor Sentiment indices may be a good contrarian predictor as they indicate significant events[20]. We can therefore ask ourselves if All EM Investor Sentiment indices are correlated with EM market returns and, when appropriate, if such indices cause these returns.

[20] However, we have to keep in mind that, even in case of important events, a matter of weeks and even months will be required for the market to move in the contrarian direction.

5.2. The link between Investor Sentiment indices and EM asset returns

There is a long-running debate in financial economics about the possible effects of Investor Sentiment on asset prices[21]. Therefore, we want to know if our All EM Investor Sentiment indices, *i.e.*, All EM Investor Sentiment index as a whole, All EM bond Investor Sentiment index and All EM equity Investor Sentiment index, are linked to EM asset returns. To achieve this, we proceed in two steps. Initially, we start by testing the correlations between our All EM Investor Sentiment indices and EM asset returns, namely equity, bond and foreign exchange markets. Secondly, we want to find out if our All EM Investor Sentiment indices cause the returns of such markets. Since macroeconomic surprises are theoretically supposed to have an impact on asset returns, we include the Citigroup Economic Surprise Index for EMs[22] (CESI-EM hereafter) for comparison purposes. Each EM asset class, *i.e.*, equity, bond and foreign exchange markets, is approximated by the most common and relevant indices. We use the Morgan Stanley Capital International Emerging Markets index in local currencies[23] (MSCI-EM hereafter) for EM equity markets, the J. P. Morgan Government Bond Index Emerging Markets Global Diversified[24] (GBI-EM hereafter) for EM local bond markets and

[21] The literature on this subject is abundant and we just want to point out that, according to Brown and Cliff (2004) measures, Investor Sentiment correlates strongly with contemporaneous asset returns but not with future returns. However, according to Baker and Wurgler (2006) measures, Investor Sentiment correlates with next period returns but only for smaller and younger stocks.

[22] The Citigroup Economic Surprise Indices are objective and quantitative measures of economic news. They are defined as weighted historical standard deviations of data surprises. The indices are calculated daily in a rolling three- month window. The weights of economic indicators are derived from relative high-frequency spot FX impacts of one standard deviation data surprises. The indices also employ a time decay function to replicate the limited memory of markets. A positive reading of the Economic Surprise Index suggests that economic releases have on balance beaten consensus. The CESI for EMs is composed of 20 emerging countries: Brazil, Chile, China, Colombia, Czech Republic, Hong Kong, Hungary, India, Indonesia, Malaysia, Mexico, Singapore, South Korea, Peru, Philippines, Poland, South Africa, Taiwan, Thailand and Turkey.

[23] The MSCI-EM index is a free float-adjusted market capitalization index that is designed to measure equity market performance of EMs. As of February 2014, the MSCI-EM index consists of the following 21 EM country indices (weights): Brazil (9.9%), Chile (1.6%), China (19.9%), Colombia (1%), Czech Republic (0.3%), Egypt (0.2%), Greece (0.6%), Hungary (0.2%), India (6.3%), Indonesia (2.5%), Korea (16%), Malaysia (3.9%), Mexico (5.3%), Peru (0.5%), Philippines (1%), Poland (1.8%), Russia (5.9%), South Africa (7.4%), Taiwan (11.9%), Thailand (2.3%) and Turkey (1.5%)

[24] The GBI-EM Global Diversified is the most widely used index to capture a diverse set of EMs that most investors can access and replicate through bonds or derivatives. It includes all eligible countries regardless of capital controls and/or regulatory and tax hurdles for foreign investors. The index incorporates a constrained market-capitalization methodology in which individual issuer exposures are capped at 10%, (with the excess distributed to smaller issuers) for greater diversification among issuing governments. As of December 2013, the following 16 EMs were part of the GBI-EM Global Diversified index (weights): Brazil (10%), Chile (0.1%),

the Morgan Stanley Capital International Emerging Markets Currency [USD] index[25] (MSCI-EM-Currency hereafter) for EM foreign exchange markets.

Table 8. Average of 52-week rolling correlations between Investor Sentiment indices and asset returns

Note: The table presents the average of 52-week rolling correlations between the four-week moving average of the All EMs Investor Sentiment indices/CESI-EM and the MSCI-EM, GBI-EM and MSCI-EM-Currency four-week moving average performances from January 2005 to January 2014. The figures in bold correspond to the correlations that we want to study in more details. In this respect, we see that the correlation between the All EMs Investor Sentiment index as a whole and the MSCI-EM is very high (59.3%) as well as the correlation with the MSCI-EM-Currency (50.6%). Interestingly, the All EMs equity Investor Sentiment index is more correlated with the MSCI-EM (60.8%) than the All EMs Investor Sentiment index as a whole. Moreover, we can draw the same conclusions about the correlation between the All EMs bond Investor Sentiment index and the GBI-EM (21.5% is greater than 21.2%).

	CESI-EM	**Investor Sentiment**	**Bond Investor Sentiment**	**Equity Investor Sentiment**	MSCI-EM	GBI-EM	MSCI-EM-Currency
CESI-EM	100%						
Investor Sentiment	2.2%	100%					
Bond Investor Sentiment	-3.6%	70.8%	100%				
Equity Investor Sentiment	2.7%	98.3%	58.4%	100%			
MSCI-EM	1.9%	59.3%	31.8%	60.8%	100%		
GBI-EM	-5.0%	21.2%	21.5%	19.0%	36.6%	100%	
MSCI-EM-Currency	8.0%	50.6%	34.5%	50.1%	73.1%	48.1%	100%

As discussed previously, we want to know if our All EM Investor Sentiment indices and the CESI-EM are correlated with the MSCI-EM, the GBI-EM and the MSCI-EM- Currency.

Colombia (3.4%), Hungary (6.2%), Indonesia (6.9%), Malaysia (10%), Mexico (10%), Nigeria (2%), Peru (1.7%), Philippines (0.5%), Poland (10%), Romania (1.5%), Russia (10%), South Africa (10%), Thailand (8%), and Turkey (9.5%).

[25] The MSCI-EM-Currency index is the first and only currency index available that sets the weights of each currency equal to the relevant country weight in the MSCI-EM index (*cf.* weights for MSCI-EM). This unique approach to weighting the currencies allows creators of index-linked products to construct investment vehicles that can be used as an efficient and convenient way to enhance or hedge currency exposure to the MSCI-EM index.

Since we use weekly data, we build long-term rolling correlations, *i.e.*, 52 weeks, between All EM Investor Sentiment indices/CESI-EM and the weekly performances of MSCI-EM, GBI-EM and MSCI-EM-Currency from January 2005 to January 2014. We summarise the average of the 52-week rolling correlations over this period in Table 8. We want to highlight the fact that the All EM Investor Sentiment indices are more correlated with asset returns than the CESI-EM. Interestingly, the All EM bond (equity) Investor Sentiment index is more correlated with the GBI-EM (MSCI-EM) than the All EM Investor Sentiment index as a whole.

In the light of the above, we want to test if our All EM Investor Sentiment indices cause the performances of equity, bond and foreign exchange markets. To this end, we perform Granger non-causality tests (Granger, 1969) to find out if our All EM Investor Sentiment indices Granger-cause asset returns. After ascertaining that our variables are stationary (ADF and PP tests), we use Akaike information criterion and Schwarz information criterion to determine the optimal number of lags that would need to be considered. The most relevant results suggest that the All EMs Investor Sentiment index, like the All EMs equity Investor Sentiment index, Granger-cause the return of MSCI-EM and the All EMs bond Investor Sentiment index Granger-causes the return of GBI-EM. However, neither the CESI-EM nor the All EMs Investor Sentiment indices Granger-cause the return of MSCI-EM-Currency.

6. Conclusion

Using the EPFR Global database, this paper provides an accurate measure of the liability side of BoP portfolio capital flows both for EM regional aggregates and EMs themselves. Contrary to BoP data, EPFR country flows are available three to nine months earlier and with a higher frequency. In an error correction framework, we show that an increase in the EPFR country flows is positively and significantly associated with an increase of BoP portfolio flows. Regarding the All EMs aggregate, the response of BoP bond flows to an increase of one dollar in EPFR bond flows is around 2.3 dollars, while it is around 1.4 dollars for equity flows. The approach here aims to simplify the existing framework on the approximation of the BoP portfolio capital flows. Against this background, the construction of Investor Sentiment indices with our simple coincident EPFR based indicator provides us some relevant information on EM asset returns. Overall, we demonstrate that the simple coincident

EPFR based indicator is a suitable candidate to practitioners who would like to proxy BoP gross portfolio capital flows in a real time setting, notably using weekly EPFR data. Lastly, EPFR data can be studied with much more granularity, *e.g.*, origin of flows, type of fund, sector allocations, type of investor, currency, etc., and represent a useful data source both for policy makers and asset managers.

Acknowledgement

In preparing this paper, I benefited from discussions with Gaëlle Le Fol and Didier Borowski, to whom I am grateful. I also wish to thank Eric Tazé-Bernard and Ling-Ni Boon for their constructive comments.

Appendix 1 – Sample coverage of BoP and EPFR portfolio capital flows

Note: The table shows the detailed availability of gross BoP capital flows and EPFR country flows. Some countries such as Malaysia, Morocco and Vietnam do not have sufficient historical data to estimate a sustainable long-term relationship. In addition, Tunisia has been disregarded since the data are at best annual frequency statistics.

	Country	BoP Flows (Liabilities)		EPFR Flows	
		Bond	Equity	Bond	Equity
Emerging Asia	China	2005Q1-2013Q4	2005Q1-2013Q4	2004M1-2013M12	2000M1-2013M12
	India	2005Q1-2013Q4	2005Q1-2013Q4	2004M3-2013M12	2000M1-2013M12
	Indonesia	2005Q1-2013Q4	2005Q1-2013Q4	2004M1-2013M12	2000M1-2013M12
	South Korea	2005Q1-2013Q4	2005Q1-2013Q4	2004M1-2013M12	2000M1-2013M12
	Malaysia	2005Q1-2009Q4	2005Q1-2009Q4	2004M1-2013M12	2000M1-2013M12
	Pakistan	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Philippines	2005Q1-2013Q4	2005Q1-2013Q4	2004M1-2013M12	2000M1-2013M12
	Sri Lanka	-	2005Q1-2013Q4	2004M11-2013M12	2000M1-2013M12
	Thailand	2005Q1-2013Q4	2005Q1-2013Q4	2004M1-2013M12	2000M1-2013M12
	Vietnam	-	2005Q1-2013Q4	2004M1-2013M12	2000M1-2013M12
Latin America	Argentina	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M312	2000M1-2013M12
	Brazil	2005Q1-2013Q4	2005Q1-2013Q4	2003M11-2013M12	2000M1-2013M12
	Chile	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Colombia	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Mexico	2005Q1-2013Q4	2005Q1-2013Q4	2004M3-2013M12	2000M1-2013M12
	Peru	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Venezuela	2005Q1-2013Q3	2005Q1-2013Q3	2004M4-2013M12	2000M1-2013M12
Emerging Europe	Bulgaria	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Croatia	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Czech Republic	2005Q1-2013Q4	2005Q1-2013Q4	2003M11-2013M12	2000M1-2013M12
	Hungary	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Kazakhstan	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M3	2004M4-2013M12
	Lithuania	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Poland	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Romania	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Russia	2005Q1-2013Q4	2005Q1-2013Q4	2003M11-2013M12	2000M1-2013M12
	Turkey	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
	Ukraine	2005Q1-2013Q4	2005Q1-2013Q4	2004M4-2013M12	2000M1-2013M12
Other EMs	Israel	2005Q1-2013Q4	2005Q1-2013Q4	2005M1-2013M12	2000M1-2013M12
	Lebanon	2005Q1-2013Q2	2005Q1-2013Q2	2005M6-2013M12	2000M1-2013M12
	Morocco	-	2005Q1-2011Q4	2004M4-2013M12	2000M1-2013M12
	South Africa	2005Q1-2012Q4	2005Q1-2012Q4	2003M11-2013M12	2000M1-2013M12
	Tunisia	-	-	2004M4-2013M12	2000M1-2013M12

Appendix 2 – Correlations between BoP and EPFR flows for regional aggregates

Note: The table shows that EPFR country flows tend to become increasingly correlated with BoP portfolio flows. This has been particularly true since the recent global financial crisis. Indeed, regarding the bond flows, the correlation increased from 60.6% before the crisis to 75.6% afterwards. However, the correlation between BoP and EPFR equity flows remains stable over the full sample period. We explain this by the fact that, over the full sample period, the average share of EPFR equity flows is more than a half of BoP equity flows, reflecting the long-term trend in correlation over time.

Emerging Asia	Bond Flows	Equity Flows
Full Sample	**55.9%**	**74.8%**
Q1 2005 to Q3 2008	39.7%	54.2%
Q4 2008 to Q3 2013	61.8%	83.9%

Latin America	Bond Flows	Equity Flows
Full Sample	**48.4%**	**85.3%**
Q1 2005 to Q3 2008	33.0%	86.5%
Q4 2008 to Q3 2013	42.7%	76.2%

Emerging Europe	Bond Flows	Equity Flows
Full Sample	**74.2%**	**59.5%**
Q1 2005 to Q3 2008	50.4%	58.0%
Q4 2008 to Q3 2013	76.4%	64.5%

Other EMs	Bond Flows	Equity Flows
Full Sample	**46.0%**	**43.2%**
Q1 2005 to Q3 2008	42.6%	59.6%
Q4 2008 to Q3 2013	52.1%	40.6%

Appendix 3 – Unit root tests results (ADF and PP) for BoP and EPFR flows

Note: The table presents the ADF (PP) t-statistics. The figures in bold reflect the ADF (PP) t-statistics in level. *, **, *** denote rejecting the null hypothesis that there is a unit root at the 10%, 5% and 1% level of confidence, respectively. We show that in more than two thirds of cases, the series that we study are integrated of the same order, *i.e.*, *I* (1).

Area/Country	BoP Bond	EPFR Bond	BoP Equity	EPFR Equity
All EMs	-2.75*** (-2.79***)	-4,34*** (-3.17***)	-3.71*** (-3.79***)	**-2.36**** (-4.25***)
Emerging Asia	**-5.10***** (-2.68***)	-5.36*** (-2.84***)	**-2.76***** (-3.66***)	**-2.00**** (-4.09***)
China	-4.45*** (-4.66***)	**-5.19***** (-0.92)	-5.53*** (-4.54***)	**-4.12***** (-5.51***)
India	-4.38*** **(-1.96**)**	**-2.44**** (-2.06**)	-5.97*** -3.53***	**-2.03**** **(-2.03**)**
Indonesia	-4.52*** (-4.53***)	-5.30*** (-3.05***)	-3.26*** (-6.44***)	-5.57*** (-5.57***)
South Korea	**-4.57***** (-2.21***)	-6.26*** (-2.37**)	**-2.33**** (-3.66***)	**-2.32**** (-3.75***)
Pakistan	-6.41*** (-6.41***)	-4.19*** (-3.87***)	**-3.70**** (-3.37***)	**-2.10**** (-3.90***)
Philippines	-4.52*** (-4.52***)	-4.88*** (-2.97***)	**-2.17**** (-2.72***)	-2.89*** (-2.99***)
Thailand	-3.06*** (-3.15***)	-3.72*** (-2.97***)	-2.08*** (-4.15***)	-4.66*** (-4.65***)
Latin America	-3.04*** (-3.11***)	-4.11*** (-3.34***)	-3.77*** (-3.77***)	-4.46*** (-4.46***)
Argentina	-3.97*** (-2.01**)	-3.75*** (-3.41***)	-3.07*** (-3.09***)	**-2.46**** (-4.51***)
Brazil	-5.44*** (-3.86***)	-4.37*** (-3.22***)	-3.51*** (-3.51***)	-4.53*** (-4.54***)
Chile	-4.78*** (-5.04***)	-2.58** (-3.52***)	-3.78*** (-3.79***)	**-2.16**** **(-2.25**)**
Colombia	-4.40*** (-5.89***)	-4.05*** (-3.58***)	-3.47*** (-3.47***)	-3.84*** (-4.03***)
Mexico	-3.61*** (-3.61***)	-3.43*** (-3.27***)	**-4.45***** (-5.11***)	**-2.21**** (-4.11***)
Peru	-3.95*** (-3.95***)	-4.14*** (-3.43***)	**-4.46***** **(-3.90***)**	-4.28*** (-4.29***)
Venezuela	-4.59*** (-4.82***)	-4.38*** (-3.04***)	-5.28*** **(-3.83***)**	-5.02*** (-6.33***)
Emerging Europe	-3.49*** (-3.49***)	-3.91*** (-3.00***)	**-2.85***** **(-2.02**)**	**-3.01***** **(-2.02**)**
Bulgaria	**-4.28***** **(-4.09***)**	**-2.47**** **(-2.06**)**	-1.99** **(-4.13***)**	**-3.71**** (-4.56***)
Croatia	-7.11*** (-6.93***)	0.53 (-4.29**)	**-1.83*** **(-1.82*)**	**-4.75***** **(-3.71***)**

Czech Republic	-4.66***	**-2.41****	**-1.99****	**-3.11*****
	(-4.94***)	(-3.08***)	**(-3.64***)**	**(-2.57**)**
Hungary	**-2.47****	-1.64*	-1.97**	**-3.93*****
	(-3.63***)	(-3.32***)	**(-2.25**)**	**(-3.22***)**
Kazakhstan	**-2.01****	-5.00***	**-5.40*****	**-2.75****
	(-3.45***)	(-3.13***)	**(-2.13**)**	**(-2.12**)**
Lithuania	-5.15***	-0.63	**-2.81*****	-4.06***
	(-3.80***)	(-4.12***)	**(-2.83***)**	**(-1.96**)**
Poland	-4.39***	-4.34***	-4.75***	**-2.50****
	(-4.46***)	(-2.99***)	(-4.77***)	**(-2.31**)**
Romania	-2.15**	-1.83*	-3.06***	-3.71***
	(-5.83***)	(-1.88*)	(-3.06***)	(-3.71***)
Russia	-3.16***	-3.53***	**-2.13****	**-2.88*****
	(-3.16***)	(-2.75***)	**(-2.32**)**	**(-2.11**)**
Turkey	-3.70***	-4.09***	-5.40***	**-2.26****
	(-3.70***)	(-2.87***)	(-4.80***)	(-4.11***)
Ukraine	-5.25***	-3.25***	-3.63***	**-4.83*****
	(-3.46***)	(-3.19***)	(-3.70***)	**(-2.73***)**
Other EMs	**-7.01*****	-4.02***	**-2.52****	-4.14***
	(-4.02***)	(-3.79***)	(-4.38***)	(-4.15***)
Israel	**-2.03****	-6.04***	**-6.79*****	**-4.03*****
	(-2.83***)	(-2.52**)	**(-3.94***)**	**(-2.26**)**
Lebanon	-5.78***	**-3.84****	**-1.98****	**-2.86*****
	(-4.57***)	(-2.61**)	**(-2.05**)**	**(-2.14**)**
South Africa	**-4.05****	-1.68*	**-2.20****	-4.49***
	(-6.21***)	(-3.91***)	(-3.45***)	(-4.49***)

Appendix 4 – Cointegration tests results (ADF and PP) for BoP and EPFR flows

Note: The table presents the ADF (PP) t-statistics on the estimated residuals $\epsilon_{it} = Y_{it} - \hat{\beta}_i X_{it} - [\hat{\alpha}_i]$ where i denotes the different countries and regional aggregates, t denotes time, ϵ is the error term from OLS regressions of BoP gross portfolio capital flows, Y , on EPFR flows, X , $\hat{\beta}$ is the estimated cointegrating coefficient and $\hat{\alpha}$ is the estimated intercept (only if it is statistically significant). The figures in bold reflect the ADF (PP) t-statistics on the estimated residuals in level. *, **, *** denote rejecting the null hypothesis that there is a unit root at the 10%, 5% and 1% level of confidence, respectively. OLS denotes the fact that we estimate the OLS regression $Y_{it} = [\alpha_i] + \beta_i X_{it} + \varepsilon_{it}$. In this case, we don't need to test the stationarity of the estimated residuals. We see that more than 70% of the series are cointegrated, almost 15% are estimated in a simple OLS framework while about 15% are not considered because the variables are not integrated of the same order or because there is no cointegration relationship. At this point, it is interesting to note that the series which are not considered are mainly equity flows, more specifically toward small EMs. In fact, it is difficult to establish a cointegration relationship (or at least a simple linear relationship) when BoP flows are low and therefore EPFR flows (which are a sample of total flows) are even lower for the smaller EMs of the study.

Area/Country	ϵ_{it}^{Bond}	ϵ_{it}^{Equity}
All EMs	**-3.14*** (-1.94*)**	**-1.95* (-1.95*)**
Emerging Asia	**-5.10*** (-2.27**)**	**-2.49** (-1.72*)**
China	OLS	**-2.14** (-2.27**)**
India	**-1.99** (-1.99**)**	*-4.26*** (-2.06**)*
Indonesia	**-2.91*** (-2.81***)**	-2.71*** **(-2.66***)**
South Korea	**-4.69*** (-2.19**)**	**-2.98***** (-2.93***)
Pakistan	*-6.39*** (-6.39***)*	**-4.86*** (-1.79*)**
Philippines	**-2.79*** (-1.84*)**	*-3.35*** (-3.47***)*
Thailand	**-2.16** (-2.31**)**	*-4.08*** (-4.15***)*
Latin America	**-4.67*** (-2.01**)**	-2.10** **(-1.93*)**
Argentina	*-6.09**** **(-2.02**)**	*-4.43*** (-4.56***)*
Brazil	**-4.67*** (-1.87*)**	**-2.25** (-1.74*)**
Chile	*3.69*** (-5.36***)*	*-6.29*** (-6.62***)*
Colombia	**-10.72*** (-3.07***)**	**-3.96*** (-1.72*)**

Mexico	**-4.90*** (-1.93*)**	**-1.86* (-2.35**)**
Peru	**-2.32** (-2.37**)**	***-4.87*** (-3.72***)***
Venezuela	**-2.19** (-2.35**)**	-5.28*** **(-3.83***)**
Emerging Europe	**-2.45** (-2.61**)**	OLS
Bulgaria	OLS	**-2.96*** (-2.97***)**
Croatia	**-3.10*** (-3.28***)**	OLS
Czech Republic	-4.90*** **(-2.20**)**	OLS
Hungary	**-2.85*** (-1.86*)**	OLS
Kazakhstan	*-3.66*** (-3.61***)*	OLS
Lithuania	*-5.39*** (-3.38***)*	OLS
Poland	**-2.52** (-2.11**)**	*-5.22*** (-5.23***)*
Romania	**-2.06** (-3.06***)**	**-2.94***** (-3.30***)
Russia	**-3.42*** (-2.47**)**	OLS
Turkey	**-3.80*** (-2.53**)**	**-2.07** (-2.33**)**
Ukraine	*-5.04*** (-4.39***)*	***-4.05*** (-2.15**)***
Other EMs	**-3.06*** (-2.09**)**	-4.68*** (-4.68***)
Israel	**-2.02** (-1.86*)**	OLS
Lebanon	**-1.71* (-1.99**)**	OLS
South Africa	**-2.10** (-3.11***)**	**-5.01***** (-5.11***)

Appendix 5 – Estimates for large EMs (USD billion, four-quarter moving sum)

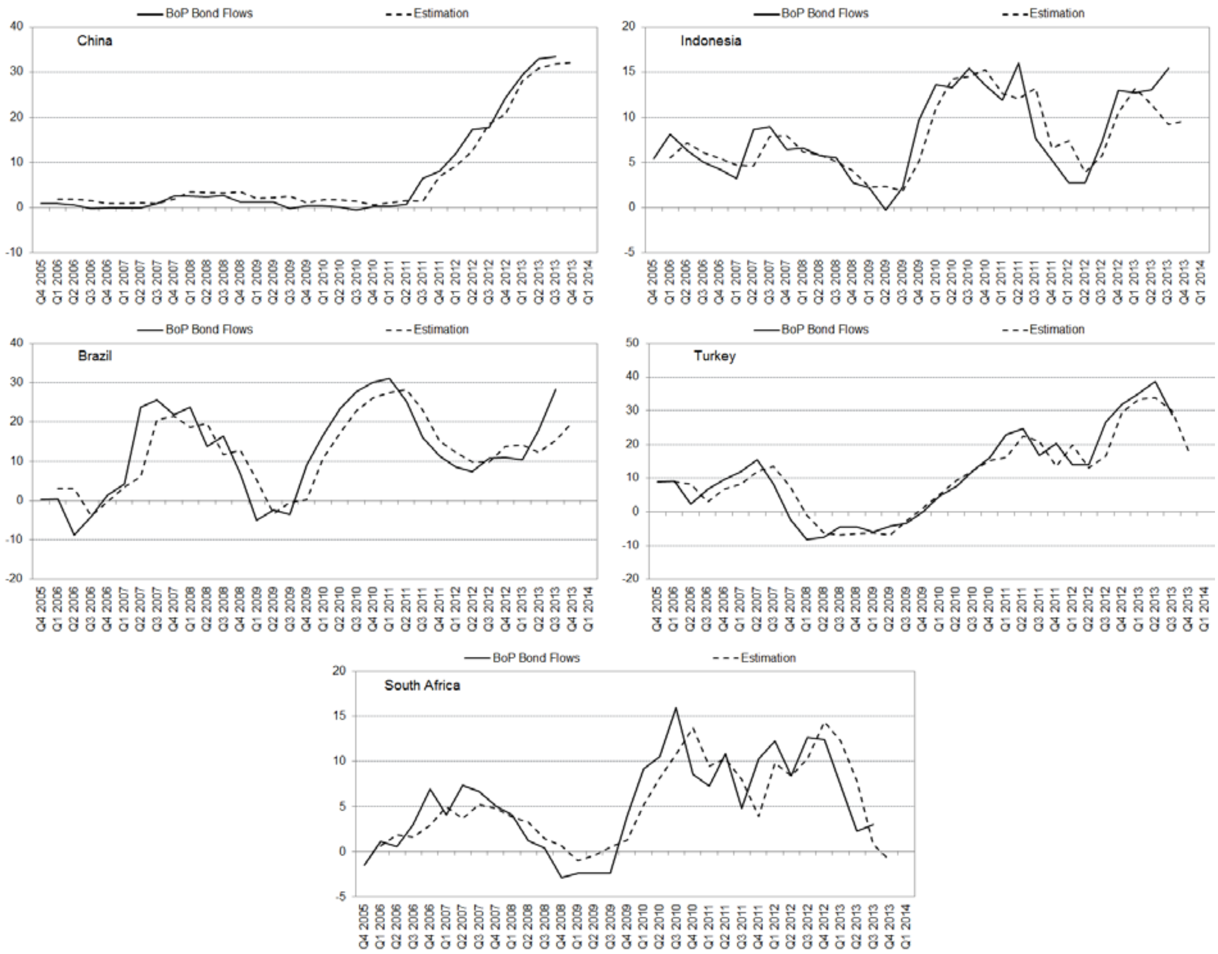
Note: The table presents the results of the ECM $\Delta Y_{it} = \gamma_i \Delta X_{it} + \delta_i \epsilon_{it-1} + \nu_{it}$ and the coefficient β of the OLS $Y_{it} = [\alpha_i] + \beta_i X_{it} + \varepsilon_{it}$. Standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level of confidence, respectively. For the simple OLS regression, estimates are made between Q4 2005 and Q4 2012. We want to emphasize that δ should be significantly negative. Otherwise, the ECM regression is not valid. Moreover, δ measures the speed at which prior deviations from equilibrium are corrected. Finally, if $X \rightsquigarrow I(d1)$ and $Y \rightsquigarrow I(d2)$ (with $d1 \neq d2$ and $d_j \in \mathbb{Z}^+$ for $j = \{1,2\}$), then we do not estimate any model to avoid spurious regression because the variables which are integrated of a different order cannot be cointegrated.

Dependent Variable: *D(BoP Bond)*

Q1 2006 - Q3 2013

Variable / Country	China	Indonesia	Brazil	Turkey	South Africa
γ_i		1.725***	2.548***	3.564***	3.209***
		(.522)	*(.808)*	*(1.072)*	*(1.072)*
δ_i		-0.412**	-0.282**	-0.273**	-0.486***
		(.187)	*(.133)*	*(.124)*	*(.169)*
Long-term relationship					
β_i	10.920***	1.814***	1.976***	7.220***	2.384***
	(.891)	*(.267)*	*(.567)*	*(.804)*	*(.500)*
Number of Observations	32	31	31	31	31
Adj. R-Squared	0.76	0.36	0.37	0.31	0.26

Note: The figures plot the four-quarter moving sum of BoP portfolio bond flows (continuous line) and the EPFR coincident indicator for bond flows (dashed line). Each figure reflects a different country. According to the IMF terminology (2011a), we identify three global waves of capital inflows in the time interval we consider in this paper: Q4 2006 to Q2 2008, Q3 2009 to Q4 2010 and Q1 2012 to Q1 2013.



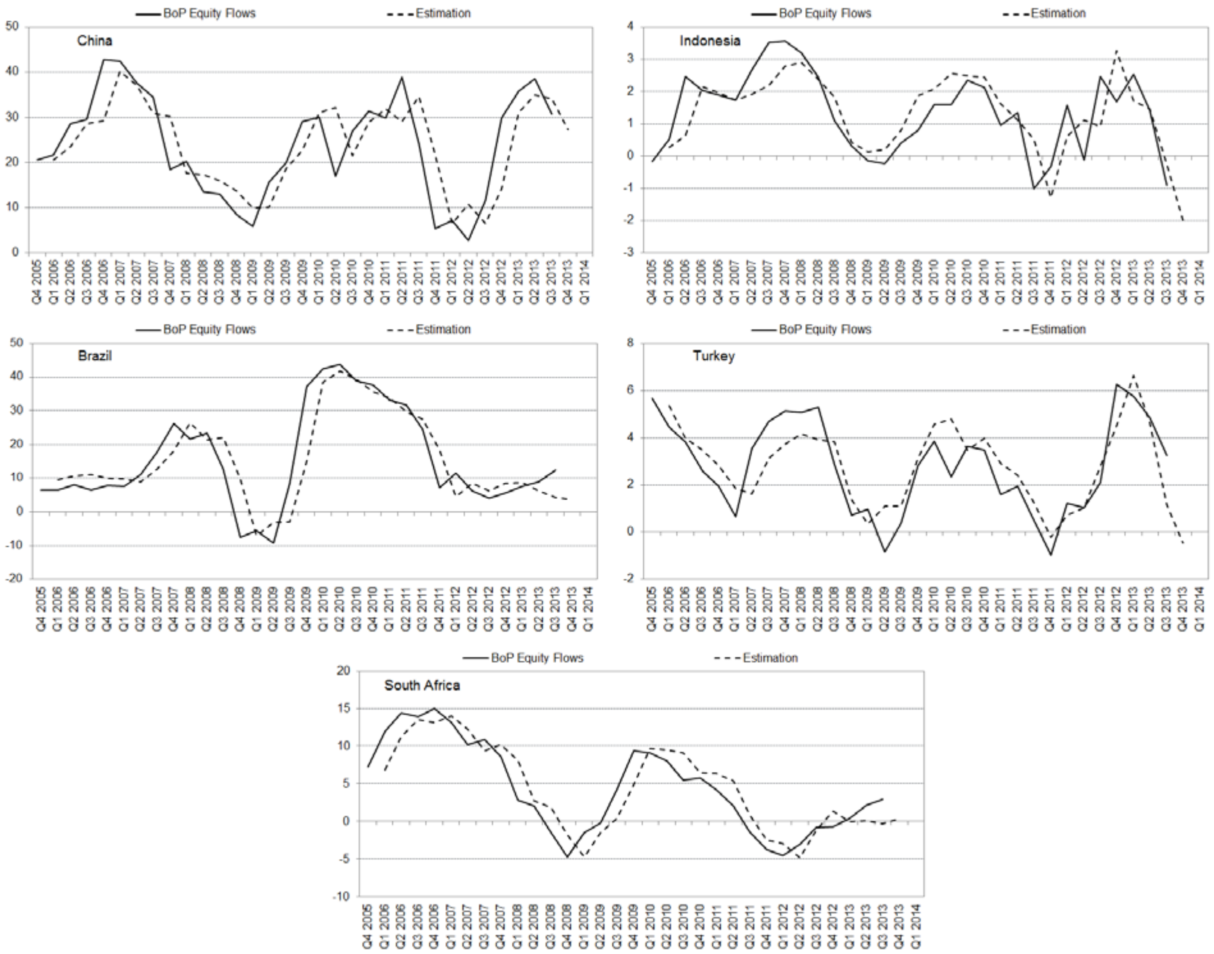
Note: The table presents the results of the ECM $\Delta Y_{it} = \gamma_i \Delta X_{it} + \delta_i \epsilon_{it-1} + \nu_{it}$ and the coefficient β of the OLS $Y_{it} = [\alpha_i] + \beta_i X_{it} + \varepsilon_{it}$. Standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level of confidence, respectively. For the simple OLS regression, estimates are made between Q4 2005 and Q4 2012. We want to emphasize that δ should be significantly negative. Otherwise, the ECM regression is not valid. Moreover, δ measures the speed at which prior deviations from equilibrium are corrected. Finally, if $X \rightsquigarrow I(d1)$ and $Y \rightsquigarrow I(d2)$ (with $d1 \neq d2$ and $d_j \in \mathbb{Z}^+$ for $j = \{1, 2\}$), then we do not estimate any model to avoid spurious regression because the variables which are integrated of a different order cannot be cointegrated.

Dependent Variable: *D(BoP Equity)*

Q1 2006 - Q3 2013

Variable \ Country	China	Indonesia	Brazil	Turkey	South Africa
γ_i	0.625***	0.686***	1.026***	1.500***	1.477***
	(.167)	*(.214)*	*(.200)*	*(.243)*	*(.408)*
δ_i	-0.351**	-0.354**	-0.292***	-0.240**	-0.075
	(.138)	*(.151)*	*(.106)*	*(.106)*	*(.065)*
Long-term relationship					
β_i	0.863***	0.362*	1.556***	0.879***	2.019***
	(.182)	*(.206)*	*(.269)*	*(.282)*	*(.508)*
Number of Observations	31	31	31	31	31
Adj. R-Squared	0.51	0.35	0.59	0.60	0.30

Note: The figures plot the four-quarter moving sum of BoP portfolio equity flows (continuous line) and the EPFR coincident indicator for equity flows (dashed line). Each figure reflects a different country. According to the IMF terminology (2011a), we identify three global waves of capital inflows in the time interval we consider in this paper: Q4 2006 to Q2 2008, Q3 2009 to Q4 2010 and Q1 2012 to Q1 2013.



Appendix 6 – Weekly and monthly EPFR country flows are quite comparable

Note: The table presents the results of the OLS $Y_{it} = \beta_i X_{it} + \varepsilon_{it}$. Standard errors are in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level of confidence, respectively. As we can see, weekly and monthly EPFR country flows are quite comparable. Indeed, *Adj. R-Squared* oscillates around 0.90 and the scale factor (represented by the coefficient β which is always significantly positive) is fairly stable for both bond flows and equity flows. β varies between 1.4 and 1.6 for bond blows while it varies between 1.1 and 1.2 for equity flows.

Variable **Area/Country**	β_i^{Bond}	*Adj. R-Squared*	β_i^{Equity}	*Adj. R-Squared*
All EMs	1.538*** *(.035)*	0.93	1.181*** *(.033)*	0.92
Emerging Asia	1.517*** *(.033)*	0.94	1.141*** *(.035)*	0.90
China	1.365*** *(.021)*	0.96	1.116*** *(.026)*	0.94
Indonesia	1.461*** *(.031)*	0.94	1.177*** *(.039)*	0.89
Latin America	1.501*** *(.038)*	0.92	1.192*** *(.033)*	0.92
Brazil	1.480*** *(.030)*	0.92	1.182*** *(.032)*	0.92
Emerging Europe	1.540*** *(.042)*	0.91	1.191*** *(.035)*	0.92
Turkey	1.404*** *(.040)*	0.91	1.109*** *(.030)*	0.93
Other EMs	1.589*** *(.043)*	0.91	1.127*** *(.044)*	0.84
South Africa	1.594*** *(.046)*	0.90	1.104*** *(.038)*	0.87

References

Ahmed, S. and A. Zlate, 2013, "Capital Flows to Emerging Economies: A Brave New World?," Working Paper No. 1081, Board of Governors of the Federal Reserve System, June.

Baker, M. and J. Wurgler, 2006, "Investor Sentiment and the Cross-Section of Stock Returns," *Journal of Finance*, Vol. 61(4), pp. 1645-1680, April.

Berthaud, F., A. Bouveret and S. Colliac, 2011, "Les flux de capitaux vers les pays émergents : enjeux et modes de régulation," Trésor Éco, No. 85, April.

Broner, F., T. Didier, A. Erce and S. L. Schmukler, 2013, "Gross Capital Flows: Dynamics and Crises," *Journal of Monetary Economics*, Elsevier, Vol. 60(1), pp.113-133, January.

Brown, G. W. and M. T. Cliff, 2004, "Investor sentiment and the near-term stock market," *Journal of Empirical Finance*, Vol. 11(1), pp. 1-27, January.

Calvo, G. A., L. Leiderman and C. M. Reinhart, 1996, "Inflows of Capital to Developing Countries in the 1990s," *Journal of Economic Perspectives*, American Economic Association, Vol. 10(2), pp. 123-139, Spring.

Calvo, G. A., A. Izquierdo and L. F. Mejia, 2004, "On the Empirics of Sudden Stops: The Relevance of Balance-Sheet Effects," Proceedings, Federal Reserve Bank of San Francisco, June.

Calvo, G. A., A. Izquierdo and L. F. Mejia, 2008, "Systemic of Sudden Stops: The Relevance of Balance-Sheet Effects and Financial Integration," NBER Working Paper No. 14026, May.

Dickey, D. and W. Fuller, 1981, "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root," *Econometrica*, Econometric Society, Vol. 49(4), pp. 1057-1072, June.

Edwards, S., 2000, "Capital Flows, Real Exchange Rates, and Capital Controls: Some Latin American Experiences," NBER Chapters, in: Capital Flows and the Emerging Economies: Theory, Evidence, and Controversies, pp. 197-254, September.

Engle, R. F. and C. W. J. Granger, 1987, "Co-integration and Error Correction: Representation, Estimation, and Testing," *Econometrica*, Econometric Society, Vol. 55(2), pp. 251-276, March.

Forbes, K. J., M. Fratzscher, T. Kostka and R. Straub, 2012, "Bubble thy neighbor: portfolio effects and externalities from capital controls," Working Paper Series No. 1456, European Central Bank, August.

Forbes, K. J. and F. E. Warnock, 2012, "Capital Flow Waves: Surges, Stops, Flight and Retrenchment," *Journal of International Economics*, Elsevier, Vol. 88(2), pp. 235-251, November.

Förster, M., M. Jorra and P. Tillmann, 2012, "The dynamics of International Capital Flows: Results from a dynamic Hierarchical Factor Model," Joint Discussion Paper Series in Economics, April.

Fratzscher, M., 2012, "Capital Flows, Push versus Pull Factors and the Global Financial Crisis," *Journal of International Economics*, Elsevier, Vol. 88(2), pp. 341-356, November.

Fratzscher, M., M. Lo Duca and R. Straub, 2012, "A Global Monetary Tsunami? On the spillovers of US Quantitative Easing," CEPR Discussion Papers No. 9195, C.E.P.R. Discussion Paper, October.

Granger, C. W. J., 1969, "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica*, Econometric Society, Vol. 37(3), pp. 424-438, July.

Hodrick, R. J. and E. C. Prescott, 1997, "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking*, Blackwell Publishing, Vol. 29(1), pp. 1-16, February.

International Monetary Fund (IMF), 2007, "Managing Large Capital Inflows," *World Economic Outlook*, Chapter 3, pp. 105-134, October.

International Monetary Fund (IMF), 2010, "Balance of Payments and International Investment Position Manual, Sixth Edition," Statistics Department, January.

International Monetary Fund (IMF), 2011a, "Recent Experiences in Managing Capital Flows: Cross-Cutting Themes and Possible Policy Framework," IMF Board Paper, Strategy, Policy, and Review Department, February.

International Monetary Fund (IMF), 2011b, "International Capital Flows: Reliable or Fickle?," *World Economic Outlook*, Chapter 4, pp. 125-163, April.

Jotikasthira, P., C. T. Lundblad and T. Ramadorai, 2009, "Asset Fire Sales and Purchases and the International Transmission of Financial Shocks," CEPR Discussion Paper No. DP7595, December.

Kaminsky, G. L., C. M. Reinhart, 1999, "The Twin Crises: The Causes of Banking and Balance-of- Payments Problems," *American Economic Review*, American Economic Association, Vol. 89(3), pp. 473-500, June.

Lo Duca, M., 2012, "Modelling the time varying determinants of portfolio flows to emerging markets," Working Paper Series No. 1468, European Central Bank, September.

MacKinnon, J. G., 1996, "Numerical Distribution Functions for Unit Root and Cointegration Tests," *Journal of Applied Econometrics*, John Wiley & Sons, Ltd., Vol. 11(6), pp. 601-618, November- December.

Magud, N. E., C. M. Reinhart and K. S. Rogoff, 2011, "Capital Controls: Myth and Reality - A Portfolio Balance Approach," NBER Working Paper No. 16805, February.

Miao, Y. and M. Pant, 2012, "Coincident Indicators of Capital Flows," IMF Working Paper, Strategy, Policy, and Review Department, February.

Phillips, P. C. B., 1987, "Time Series Regression with a Unit Root," *Econometrica*, Econometric Society, Vol. 55(2), pp. 277-301, March.

Phillips, P. C. B. and P. Perron, 1988, "Testing for a Unit Root in Time Series Regression," *Biometrika*, Vol. 75(2), pp. 335-346, June.

Raddatz, C. E. and S. L. Schmukler, 2012, "On the International Transmission of Shocks: Micro- Evidence from Mutual Fund Portfolios," *Journal of International Economics*, Elsevier, Vol. 88(2), pp. 357-374, November.

Ravn, M. O. and H. Uhlig, 2002, "On adjusting the Hodrick-Prescott Filter for the frequency of observations," *The Review of Economics and Statistics*, MIT Press, Vol. 84(2), pp. 371-375, May.

Reinhart, C. M. and V. Reinhart, 2009, "Capital Flow Bonanzas: An Encompassing View of the Past and Present," NBER Chapters, in: NBER International Seminar on Macroeconomics 2008, pp. 9-62, April.

Amundi Working Paper

WP-044-2014

November 2014