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The non-persistent relationship between foreign equity flows and emerging stock market returns across quantiles*

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ABSTRACT

We compare the performance of two state-of-the-art predictive regression methods of IVX-Wald (Kostakis et al., 2015), IVX-Quantile regression (Lee, 2016) with the traditional OLS in examining the relationship between foreign equity flows and emerging stock market returns. By doing so, we take into account not only the potential persistence in foreign equity flows, but also the exceptional behavior of the extreme foreign flow episodes. We find a robust positive relationship between equity flows and contemporaneous stock returns among emerging stock markets (especially in Asia), but little evidence for intertemporal return predictability.

Keywords: Emerging stock markets; International Capital Flows; Predictive regression; IVX filtering.

JEL classification: C22, G12, G15

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1. Introduction

How do foreign investors affect the stock movements in *Emerging Markets Economies* (EMEs)? This is a question of essential importance for both researchers and policymakers, as well as a long-standing debate in International Economics/Finance. The growing cross-border capital flows represent the most prominent form of global financial integration, the degree of which has noticeably increased over the past decades. In particular, global capital flows increased from 7% of the world GDP in 1998 to over 20% in 2007, but suffered large reversals in late 2008 and re-surged after that (Milesi-Ferretti and Tille, 2011). At the same time, stock prices in EMEs went up sharply in 2007, but dropped even more than developed markets in 2008, and recovered faster than the developed markets (Bartram and Bodnar, 2009; Yan et al., 2016). Due to this seemly coincidence, it is not uncommon to conjecture two hypotheses: 1) the sizable foreign flows have caused the stock movements in EMEs, i.e., price pressures[1]; 2) foreign investors can predict the stock movements in EMEs (Ahmed and Zlate, 2014).

Both hypotheses are plausible and rooted in the literature. On the one hand, the literature has documented a positive contemporaneous relationship between equity flows and returns[2]. On the other hand, it has been conjectured that one major motive for foreign investors is return-chasing (i.e., chase higher future returns), and higher returns in the future will attract more equity flows[3]. If this motive is true, foreign investors must have the ability to predict future stock movements in the first place.

The literature typically use OLS based methods such as vector autoregressive models to test the first hypothesis[4], while the second hypothesis has rarely been tested, probably because that the classic method (i.e., predictive regressions) for return predictability research

[1]See, for example, Tong and Wei (2011), Jotikasthira et al. (2012), Yan et al. (2016), Puy (2016), Fuertes et al. (2017).

[2]See, e.g., Brennan and Cao (1997), Griffin et al. (2004), Richards (2005), Hau and Rey (2004, 2006). Ülkü and Weber (2014), Ülkü (2015), Yan et al. (2016), Fuertes et al. (2017). Richards (2005) offers a simple story based on demand shocks to illustrate the mechanism: holding the portfolio preferences of domestic investors unchanged, decisions by foreigner investors to buy (sell) are demand shocks leading to an outward (inward) shift of aggregate demand curve and thereby an increase (a decrease) of stock prices. The market microstructure literature further paves the theoretical foundation for this hypothesis.

[3]See, for example, Bohn and Tesar (1996), Brennan and Cao (1997), Raddatz and Schmukler (2012), Curcuru et al. (2011, 2014), Fuertes et al. (2017). The return-chasing hypothesis has been embedded in various theoretical models (Brennan and Cao, 1997; Albuquerque et al., 2007, 2009; Dumas et al., 2017).

[4]See, for example, Froot et al. (2001), Bekaert et al. (2002), Griffin et al. (2004), Richards (2005), Kamin and DeMarco (2012), Forbes (2013), Yan et al. (2016).

does not suit foreign flows due to their potential persistence. It would be serious to neglect equity flows' persistence[5] because it will give rise to invalid results if equity flows are employed as a predictor in a standard predictive regression. In particular, Campbell and Yogo (2006) show that if the predictor is strongly persistent, empirical results based on standard regression models such as OLS will suffer severe size distortion leading to an over-rejection of the null hypothesis of no predictability. Since it is difficult to identify the exact degree of persistence precisely, standard unit root tests hardly provide a firm guide (Lee, 2016). To tackle this potential problem, we employ the predictive regression model based on IVX-filtering (Kostakis et al., 2015), which can handle predictor variables with various degrees of persistence.

On the other hand, the traditional OLS based methods have been criticised recently as well. Using a quantile regression model, Ghosh et al. (2014) demonstrate that international flows behave differently during normal periods and extreme episodes such as surges, stops, flight, and retrenchment[6]. To tackle this potential problem, we employ the IVX-version of quantile regression (IVXQR) of Lee (2016), which enables us to examine the predictability of stock returns across all quantiles of its conditional distribution. Both the predictive regression model with IVX-filtering and the IVX-version of quantile regression are sophisticated and flexible models, which are used for the first time in a study of international capital flows and constitutes our methodical contribution in this paper. More importantly, these two models allow us to provide a comprehensive and robust answer to the initial question of how foreign investors affect the stock movements in EMEs by ensuring that the results would not be a statistical artifact because of the persistent predictor.

We choose to focus on portfolio equity flows in this paper, as it is straightforward to conjecture that stock bubbles in EMEs were more likely to be associated with portfolio equity flows, than other types of short-term flows such as portfolio bond flows and bank flows.

[5]This persistence of capital flows is grounded in the literature. Albuquerque et al. (2007) develop a theoretical model predicting persistence as an enduring feature of foreign investors' trading, because of the heterogeneity within their group of accessing and responding to new information. In addition, foreign investors may divide their trading into small parts to reduce their trading costs brought by price pressures (Kyle, 1985). Accordingly, Froot et al. (2001) Griffin et al., (2004), Richards, (2005), Ülkü and Weber (2014), Ülkü (2015), and Fuertes et al. (2017) found empirical evidence that capital flows are auto-correlated. Although it is difficult to identify the exact degree of persistence precisely, Sarno and Taylor (1999a, b) and Fuertes et al., (2016) have identified both a persistent and a temporary component in various kinds of international capital flows.

[6] This is supported by other studies such as Rothenberg and Warnock (2011), Forbes and Warnock (2012), etc. As a result, there is a possibility to mix the different patterns capital flows across all episodes by pooling data together via the traditional OLS based methods.

Moreover, portfolio equity flows are easy to access at relatively high frequencies (at least monthly), which may not be so easy to access for other types of short-term flows such as bank flows, which are usually available at quarterly frequency (Fuertes et al., 2016). We exclude long-term capital flows such as Foreign Direct Investment (FDI) and official flows as they differ from short-term capital flows in nature (e.g., Tong and Wei, 2011; Fuertes et al., 2016). Short-term flows are more volatile and speculative, and they could rush into a country and then run out precipitously because of return-chasing. Therefore, short-term speculative capital flows are more likely to affect local financial markets than long-term flows.

To conduct our empirical analysis, we collect monthly data for 21 EMEs over 1995-2014[7]. Our data for stock prices are collected from Morgan Stanley Capital International (MSCI), and data for equity flows are from Treasury International Capital (TIC). Figure 1 plots the data of both average equity flows and stock prices of all the EMEs in our sample to enable us to have a glimpse of the correlation between these two variables. The solid black line represents an overall MSCI stock price index of the EMEs, while the dashed blue line shows the average equity flows towards all EMEs in our database, scaled by domestic GDP.

[Insert figure 1 around here]

Figure 1 seems to suggest a co-movement and a lead-lag relationship between these two variables, and this pattern becomes more evident after the early 2000s, after which the global financial market had been significantly integrated. Specifically, both equity flows (lead) and stock prices (lag) rose before the millennium, around which the dot.com bubble was present in the U.S. stock market. As this “information technology bubble” collapsed in the early 2000s, both equity flows and stock prices in EMEs dropped, reaching the bottom around late 2001. Nevertheless, a more noticeable pattern of co-movements appeared in the mid-2000s: both equity flows and stock prices surged until the outset of the global financial crisis. However, after 2008, both time series collapsed sharply and semi-simultaneously. One might observe from Figure 1 that this drop is more sizable and prolonged than any other. Finally, in the post-crisis era, equity flows and prices appear to co-move again. In sum, we observe several patterns of co-movements and a lead-lag relationship between equity flows and stock prices, which motivates our further analysis.

[7]Since most of the latest capital flow literature uses data over monthly frequency, in this paper we focus on one-month-ahead returns to keep consistency with the literature. The results do not qualitatively change when we equally divide our monthly flows into bi-weeks (or weeks) and match with biweekly (or even weekly) returns. We omit the specific results for brevity.

Our main findings can be summarized as follows. We first investigate the link between equity flows and contemporaneous returns. We start with OLS and find a significant association between these two variables among a large number of EMEs, especially among the Asian stock markets. The estimated coefficients of equity flows are mostly positive. To rule out the potential size distortion resulted from equity flows' persistence, we employ the latest IVX models. Based on the predictive mean regression of Kostakis et al. (2015), we confirm that our results are not a statistical artifact owing to a persistent regressor. Based on the IVX-version of quantile regression of Lee (2016), we also show that equity flows are generally significant across a wide range of quantiles.

Secondly, we investigate the association between equity flows and one-month-ahead stock returns, in which practitioners might be more interested. We find little evidence for the stock return predictability of foreign investors in EMEs. Only a few countries, namely Poland and South Africa, show strongly significant estimates. The disappearance of equity flows' significance is in line with the findings of Richards (2005), which finds a significant price impact associated with foreigners' trading on six Asian EMEs. However, this price pressure typically disappears within days. Similarly, in our study, it is likely that equity flows' price impact is short-term so that they contain limited information to predict one-month-ahead returns. In addition, equity flows' estimated signs are usually negative[8].

Finally, we also conduct an out-of-sample analysis, and find that only equity flows in Poland can outperform the benchmark model. In summary, this study finds a significant contemporaneous association between equity flows and international equity flows. Although the monthly equity flows appear to contain limited (if any) information to forecast one-month-ahead stock returns in EMEs, our empirical tools could be a fascinating venue for future research using equity flows' data of higher frequency (such as weekly or even daily), whose persistence could be significantly stronger (e.g., Ülkü and Weber, 2014; Ülkü, 2015).

The remainder of this paper is organized as follows. Section 2 discusses our empirical methodology, and Section 3 describes our data set as well as summary statistics. Section 4 presents our empirical results. Section 5 concludes. Section 6 is the appendix section, which discusses our filtering approach, and gives a brief description of recent predictive regressions models based on IVX-filtering.

[8] This finding is in line with the literature (e.g., Ülkü and Weber, 2014; Ülkü, 2015; Yan et al., 2016; Fuertes et al., 2017).

2. Model estimations based on IVX

This section presents two unbiased approaches to tackle the potential persistence of capital flows: The mean regression with IVX-Wald test proposed by Kostakis et al., (2015), and the Quantile regression IVX-QR approach proposed by Lee (2016).

2.1. Mean regression: IVX-Wald (Kostakis et al., 2015)

For the conditional mean regression of stock return predictability, we use the model proposed by Kostakis et al. (2015). Denote all the demeaned variable as: $Y_t = y_t - \bar{y}_n$, $X_t = x_t - \bar{x}_{n-1}$, and $\xi_t = \varepsilon_t - \bar{\varepsilon}_n$, and then the resulting demeaned regression matrices would be: $\underline{Y} = (Y_1', \dots, Y_n')'$ and $\underline{X} = (X_1', \dots, X_n')'$. Similarly, we denote the (undemeaned) instrument matrix as $\underline{Z} = (Z_1', \dots, Z_n')'$. Then it is convenient to rewrite the model in Equation (A.1) as follows:

$$Y_t = AX_{t-1} + \xi_t. \tag{1}$$

The IVX estimation of A from the predictive regression (1) is analogous to a two-stage-least-squares estimator based on the instrument with (MI) persistence in (A.4). Formally, it is:

$$\tilde{A}_{IVX} = \underline{Y}'\tilde{Z}(\underline{X}'\tilde{Z})^{-1}. \tag{2}$$

Kostakis et al. (2015) further show that IVX-estimators are asymptotically mixed normal, and the linear restrictions on the coefficient matrix A from (A.1) or (1) could be tested by a standard Walt test, which is easier than earlier models based on the Bonferroni method.

2.2. Quantile regression IVX-QR (Lee, 2016)

While most of the literature focuses on predicting the conditional mean of stock returns, it is interesting to investigate the predictability at each quantile across the whole conditional distribution of returns[9]. Firstly, financial data are typically known as having heavy tails and skewed distributions. Such features might imply potentially greater predictability at certain quantiles rather than only the median (Lee, 2016). Secondly, in many areas of financial economics, it might be even more interesting to examine the entire return distribution or specific parts of the distribution such as tails. For instance, risk managers may pay more

[9] This idea has been used in other topics, see e.g., Cenedese et al. (2014), who use it for a different application but try to capture the same idea, i.e., the economic value of different betas across quantiles. We thank a referee for pointing it out.

attention to the left tail. Thirdly, the literature reports that equity flows could be pro-cyclical, which implies that equity flows might have a more substantial impact on some particular quantiles (such as the two tails). For example, Broner et al. (2006) find that international mutual funds tend to increase (decrease) their weights of countries in which they have a large (small) portfolio weights when the funds are doing relatively well (poorly). Raddatz and Schmukler (2012) also find that both individual investors and fund managers tend to take too much risk during good times. However, they would run and retrench quickly when shocks hit the financial system. Therefore, it is interesting to examine whether equity flows exhibit a more significant predictability conditional on turbulent episodes—two tails of returns distribution. To that end, the application of Quantile Regression (QR) in Koenker and Basset (1978) has some merits.

However, QR faces the same problem of non-standard distortion as the mean regression does if the regressor is highly persistent. To solve this problem, Lee (2016) adopts the same IVX instrumentation (Philllips and Magdalinos, 2009) and develops the IVX-quantile regression (IVX-QR) allowing for persistent predictors. To formalize this model, let us first consider a linear predictive QR model:

$$Q_{y_t}(\tau) = \mu_\tau + A_\tau x_{t-1} + \varepsilon_t, \tag{3}$$

where $Q_{y_t}(\tau)$ is a conditional quantile of the dependent variable (stock returns). Then the ordinary QR estimator has the form:

$$\hat{A}_\tau^{QR} = argmin_A \sum_{t=1}^{n} \rho_\tau (y_t - Ax_t), \tag{4}$$

where $\rho_\tau(u) = u\big(\tau - 1(u < 0)\big), \tau \in (0,1)$ is the asymmetric QR loss function and u is QR the residual.

The IVX-QR estimation starts with a de-quantile procedure, which is analogous to the demeaning process in the mean regression. Formally, we remove the intercept term in (3):

$$y_{t\tau} = A_\tau x_{t-1} + \varepsilon_{0t\tau}, \tag{5}$$

where $y_{t\tau} \coloneqq y_t - \hat{\mu}_\tau^{QR}$. Based on the IVX-instrument $\widetilde{z}_t$ from Equation (A.5), the IVX-QR estimator is:

$$\hat{A}_\tau^{IVXQR} = \arg inf_A \frac{1}{2} \left(\sum_{t=1}^{n} m_t(A)\right)' \left(\sum_{t=1}^{n} m_t(A)\right), \tag{6}$$

where $m_t(A) = \tilde{z}_{t-1}(\tau - 1(y_{t\tau} \leq A\, x_{t-1}))$. Lee (2016) shows that the resulting test statistics follows a chi-square limit distribution, which is empirically easy to compute.

3. Data and descriptive statistics

Our dataset covers 21 EMEs from January 1995 to December 2014. We start with January 1995 because some countries' data (e.g., Czech and Hungary) are not available before this time. We end our sample at December 2014, one year earlier than the time of writing (i.e., January 2016), to alleviate the potential data revisions to equity flows and aggregate prices[10]. We divide these countries into four groups according to their regions. The first group consists of seven countries from Asia: China, India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand. The second group includes six Latin American countries: Argentina, Brazil, Chile, Colombia, Mexico, and Peru. The third group contains four EMEs from emerging Europe: Czech, Hungary, Poland, and Russia. Finally, we classify the remaining countries in our sample into one group: Egypt, Morocco, Turkey and South Africa.

The stock returns, defined as logarithmic monthly changes in dividend-adjusted MSCI global stock indices in U.S. Dollars (USD)[11], are collected via Bloomberg. We compute excess returns as the difference between monthly stock returns and the one-month Treasury bill rate.

We obtain monthly international equity flows from the U.S. to the 21 EMEs. We collect the data from the Treasury International Capital (TIC) database of the U.S. Treasury Department, following the extant literature (e.g., Sarno et al., 2016; Fuertes et al., 2016).

We use gross flows rather than net flows to avoid possible contamination from the behavior of domestic investors (Rothenberg and Warnock, 2011; Forbes and Warnock, 2012).

[10] Ideally, we should use all the observations available if all variables can be observed contemporaneously without any revisions. Unfortunately, this is not the case in reality. Specifically, all equity flows and CPI indices are known with lags and are subject to revisions over time. In other words, stock indices are known in real time but equity flows and aggregate prices are not. Therefore, in reality the two sets of data are not observed contemporaneously. We are not aware of a better way to deal with this problem and most of the extant studies suffers from it as well. We thank a referee for pointing it out.

[11] Our results do not qualitatively change even if we use ex-dividend stock indices. We omit the results for brevity.

As the extant literature mostly discusses the impact of foreign investors who are domiciled in developed markets but invest in the stock markets of EMEs (e.g., Broner et al., 2006 and Jotikasthira et al., 2012), we focus on gross inflows, defined as the net of U.S. purchases of domestic stocks and U.S. sale of domestic assets (Forbes and Warnock, 2012). Therefore, a positive entry indicates an inflow into an EME from the U.S. Finally, all flows are in millions of USD, and we deflate each time series by U.S. CPI to convert it into real values.

[Insert Table 1 around here]

Table 1 reports the descriptive statistics. Excess returns average about 0.506% across countries, and their standard deviations are on average 9.81%, indicating the high stock volatility in EMEs. As for flows, they average about 25.306 million USD and 0.006 % of nominal GDP across countries, and their high standard deviations reveal equity flow's volatile nature. Across 21 EMEs, average standard deviations are 126.067 million USD (when flows are measured in USD) and 0.046 % (when scaled by domestic GDP). We do not report the traditional Unit root test results, as Lee (2016) points out that "*Unit root tests do not provide a firm guidance on the discrepancy between I(0), near or exact unit root processes*."

4. Empirical results

To assess the predictability of stock returns from international equity flows, we present our empirical results in two parts. In the first part, we report our results of in-sample tests. In the second part, we show the out-of-sample tests' results.

4.1. In-sample tests

In this sub-section, we first investigate the contemporaneous relationship and after that move to the lead-lag relationship between current flows and one-month-ahead returns.

4.1.1 Contemporaneous returns

We start our empirical investigation with the contemporaneous relationship between equity flows and stock returns. Panel A of Table 2 reports our results based on OLS, which suggests that equity flows significantly affect stock returns *contemporaneously*: 9 out of 21 EMEs display significant estimates at 10% level, and among them 8 are significant at 5% level. For these 9 EMEs, their estimated coefficients are all positive. Taking India for example, if equity flows increases by 100 Million USD (in real value), its domestic stock return is likely to increase by 0.7%. This positive sign is consistent with the price pressure stories arguing that the equity flows rush into an EME could drive up stock prices quickly (e.g., Richards, 2005).

Panel A of Table 2 suggests that equity flows have a heterogeneous impact among different regions. Specifically, the Asian countries are more severely affected. Among the 7 Asian EMEs in our sample, 4 (India, Malaysia, Philippines, and Thailand) display a significant slope estimate of equity flows. As for the other 14 EMEs, we also observe significant estimates from Brazil, Czech, Russia, Egypt and South Africa. However, these countries are spread across different regions (Latin America, East Europe, and others), and no other region contains such a considerable percentage of significant estimates as Asia does. A number of empirical studies—e.g., Richards (2005) and Tillman (2013)—also support the observation that Asian equity flows significantly affect the local stock prices. Nevertheless, few theoretical studies clarifies why this observation is particularly significant in Asia compared to other regions.

[Insert Table 2 around here]

If equity flows are persistent or belong to the I (1) space, empirical results based on OLS would be invalid. Worse, it is also empirically challenging to identify the exact degree of persistence, which also confuses the validity of OLS estimates. Therefore, Panel B of Table 2 reports our results based on IVX-filtering predictive regression of Kostakis et al. (2015), which remains valid when handling predictors with various degrees of persistence.

One observes that the results in Panel B of Table 2 are mostly similar to those in Panel A of Table 2. Again, 9 (8) out of 21 EMEs show significant coefficient at 10% (5%) level. The geographical pattern stays similar. Asian countries remain the most significant group that displays significant estimates. This similarity suggests that the significant estimates of equity flows are not statistical artifacts due to the predictors' persistence. Therefore, our results (based on IVX-filtering technology) confirm the significant association between international Equity flows and contemporaneous stock returns in EMEs.

IVX-QR

Our empirical results based on predictive mean regression can be informative. However, given our previous discussion of equity flows' pro-cyclical nature, we also examine the entire return distribution or specific parts of the distribution such as tails and center.

Asian

Panel C of Table 2 presents our empirical results from the 10^{th} to the 90^{th} quantile based on IVXQR. One can still observe that the equity flows' effect on stock returns is the strongest among the Asian EMEs. Out of the 7 Asian countries in our samples, the 4 EMEs (India, Malaysia, Philippines, and Thailand) where equity flows are significant in the conditional mean regression all display significant results across a wide range of quintiles. Equity flows in India appear significant through the returns' conditional distribution except for the 75^{th} quantile. The magnitude of their estimated coefficient varies from 0.005 to 0.010, and it is slighter more substantial in the left tails (10^{th} to 50^{th}). Indian equity inflows have a more significant price impact conditional on episodes of relatively low returns. Equity flows into Thailand have positive and significant coefficients from the 25^{th} to the 75^{th} quantile. Moreover, we observe a more pervasive effect from Malaysia and Philippines: equity flows towards these two countries possess positive and significant coefficient estimates across all quintiles reported (10^{th} to 90^{th}).

More interestingly, IVXQR detects predictability in some specific part of returns distribution, which has been overlooked by the conditional mean regression. For instance, equity flows to Indonesia lack significance in both of the conditional mean regressions, as shown in Panel A and B of Table 2. Nevertheless, our results based on IVXQR (in Panel C of Table 2) report positive and strongly significant coefficients in the left tail (from 10th to 25th). Indonesian equity inflows eventually become insignificant in the upper quantiles. This finding based on quantile regression suggests a heterogeneous effect across different parts of returns' distribution, and thereby imply that the price impact of equity inflows into Indonesia might be more substantial when returns are relatively lower. As international investors retreat from the local stock markets quickly during bad times (e.g., Raddatz and Schmukler, 2012), the heterogeneous price effect found in this study could be in line with this pro-cyclical nature.

Latin America

Table 2 also shows that equity flows into Latin America have a considerably smaller impact on returns, than the ones into Asia. Among the 6 Latin American EMEs, only equity flows to Brazil are significant across the whole conditional distribution. Moreover, those coefficients are all positive. This observation is once again in line with theory, as we previously discussed in Section 1. As for some other Latin American countries, equity flows appear with significant estimates in a few quantiles in one tail of returns' distribution. For example, equity flows to Chile are significant in the 10th and the 25th quantiles, which suggests that equity flows have a stronger contemptuous predictability of returns when returns are relatively low. However, the pattern in Peru is completely the opposite: equity flows are only significant when returns are relatively high ($\tau = 75th\ and\ 90th$). For these two countries, equity flows' price impact is significant only at the two tails of returns' conditional distribution, which again implies that equity flows might have a stronger impact on returns during good or bad times.

East Europe

Turning to the East European countries, Equity flows to the Czech Republic and Russia are still significant across a considerable amount of quantiles. These observations are consistent with the results from the conditional mean regressions (shown in Table 2). In particular, equity flows to Russia are significant across the whole distribution: they possess positive and statistically significant coefficients from the 25th to the 90th quantile. However, equity flows' price impact is asymmetric in Czech, as we only observe significant estimates in the right part of the returns' conditional distribution implying episodes when the stock returns are booming.

Others

The bottom panel of Table 2 shows the results for the other EMES: mainly countries from the Middle East and Africa. Firstly, equity flows to Egypt and Morocco are insignificant in the conditional mean regressions (as shown in Panel A and Panel B of Table 2). However, our results based on IVXQR suggest that equity flows to these two EMEs might possess more predictability in some specific parts of the distribution. Starting with Egypt, equity inflow has a positive effect on returns conditional on episodes when returns are low (at lower quantiles), but this effect decreases and becomes insignificant after the 50th quantile. For Morocco, Turkey, and South Arica, equity flows' effect (on returns' predictability) is not significant at the left tail but the right tail of the conditional distribution. For instance, at the 75th percentile, a 10 million USD increase of equity flows to Morocco would be associated with a 3.0% increase in returns. This implies a significant price impact of equity flows to Morocco, which is a relatively small economy compared to the other EMEs in our sample. Overall, for these EMEs, quantile regression suggests more predictability in the two tails.

In summary, our results suggest that equity flows towards Asian countries significantly affect the local stock returns contemporaneously. Among all the 7 countries, only China and

Pakistan display no significant coefficient in any quantile reported. Furthermore, compared to the outcomes from the previous two conditional-mean regressions, our results based on IVX-QR show two additional implications: first, for some countries (especially those in Asia), equity flows affect equity prices during both booms and busts (throughout the whole conditional distribution of returns). Second, for a few other countries, predictability is only found during episodes of either expansion or contradiction. For instance, predictability in the Egyptian stock markets is only found in returns' lower quantiles; this shows the association between flows and returns only exists when returns are relatively low. Likewise, we could only observe stock return predictability in Peru and Czech during good times—that is, the upper quantiles.

4.1.2 One-month-ahead returns

Our results on the contemporaneous relationship may not be enough for the practitioners, who are more interested in whether international equity flows can predict future stock returns. To that end, we report the results of one-month-ahead predictability based on the same set of empirical models (OLS, IVX-Wald, and IVXQR) used previously. We start with OLS estimates.

OLS

The Panel A of Table 3 shows the one-month-ahead results based on OLS. One might observe several striking findings: firstly, the predictability mostly disappears. This is most prominent in Asian markets, that equity flows lack significance in all of the seven Asian EMEs. This observation is a sharp contrast to our results reported in Table 2, where contemporaneous equity flows display significantly positive estimates in four out of seven Asian markets. This is probably due to the short-term nature of equity flows' price impact. Richards (2005) uses daily data to investigate the link between net purchases of foreigners and returns in some Asian stock markets. He found that inflows have impacts on prices even beyond the day of inflow, but most of this impact is complete within a few days. This finding might help to explain our empirical results here: when international equity inflows enter the domestic stock markets, they drive up stock returns contemporaneously, but their impact might perish within days. Therefore, there is no significant link between equity flows and one-month-ahead returns.

Another somewhat surprising observation is that among the countries where equity flows are significant (Colombia, Poland, and South Africa), the estimated coefficients for equity flows are all negative. Take Poland for instance: if foreign equity inflow goes up by 10 million real USD, its domestic stock returns decrease by 0.6%. There are two interpretations of the negative signs of equity flows' coefficient in the literature. On the one hand, there could have been an overshooting of stock returns in response to equity flows, such that the price impact is gradually reversed in later months. For instance, Cenedese and Mallucci (2016) show that the covariance between expected flows and returns turns negative in the long-run, and this effect is exceptionally strong for EMEs. On the other hand, future stock returns' reduction might be a consequence of foreign investors' portfolio rebalancing. Specifically, when the local stock returns are driven up by the international equity flows, foreign investors might rebalance their portfolio by reducing their equity holdings in the underlying market to hedge against foreign exchange risk. Such behaviors might lead to equity outflows, and thereby a reduction of stock returns (see, e.g., Hau and Rey, 2004, 2006; Curcuru et al., 2011, 2014; Fuertes et al., 2017).

IVX-Wald;

[Insert Table 3 around here]

To ensure that our results are not a statistical artifact because of a persistent regressor, we again employ the IVX-Wald test of Kostakis et al. (2015), whose results are displayed in the Panel B of Table 3. Compared to OLS results in Panel A of Table 3, firstly, we notice the weak significance of Colombian equity flows disappears. This implies that the significance reported in Panel A of Table 3 might result from size distortion owing to persistent equity flows. However, the significance of equity inflows into Poland and South Africa remain, and both of their estimated coefficients are negative. Therefore, their results might be valid, and we may interpret them similarly as we did in the OLS estimates.

IVX-QR;

To explore more predictability from the whole distribution of one-month-ahead stock returns, we employ the IVXQR of Lee (2016) and present the results in Panel C of Table 3. For the two countries (Poland and South Africa) where equity flows could significantly predict one-month-ahead stock returns in the conditional mean regressions, their equity flows again display significant and negative coefficients across some quantiles. At 5% level, the only exception is that, equity flows to Russia are positive and significant at the 10^{th} quantiles. For the rest of the EMEs, equity flows are insignificant, and this is consistent with our previous results.

In summary, the one-month-ahead predictability is surprisingly different from the contemporaneous relationship. Firstly, equity flows' significance largely disappears and their price impact could be short-term. Equity flows could drive up contemporaneous prices, but their impact might perish quickly (Richards, 2005). This observation is especially prominent among the Asian countries, where equity flows significantly affect contemporaneous returns. Secondly, equity flows' estimated coefficients are found to be negative. We show that this observation might be an overshoot of returns in response to international equity flows.

4.1.3. Robustness

Our results are robust to adding global factors such as VIX and TED, but we choose to omit these results for brevity. Below we report results from a few robustness checks by changing the specifications of equity flows into: (1) net flows; (2) gross inflows over domestic GDP.

We repeat our previous regressions with net flows, and find that the results of contemporaneous predictability are similar to those based on gross inflows (as shown from Tables 4 -5). Nevertheless, we observe even less evidence of one-month-ahead predictability—both in sample and out-of-sample, both through the conditional mean and conditional quantile regressions. Therefore, such results may again justify our choice of gross inflows.

[Insert Table 4 – 5 around here]

Equity flows in our main empirical analysis are measured in USD (deflated by CPI). However, Curcuru et al. (2011) argue that such a specification may lead to confounding results because of the wealth effect: if financial wealth is growing—which is a reasonable assumption—a dollar today may suggest significantly different value in ten years. To investigate this possibility, we scale equity flows with gross domestic productivity (GDP), which is a standard method from the literature (e.g., Yan et al., 2016). Nevertheless, we refrain from choosing this specification as the baseline specification in our main analysis because GDP data are available at much lower frequency. The results are reported from Tables 7 to 8. One can observe that the results are similar with those from our main analysis; such findings may imply a relatively small impact of the wealth effect on our main analysis.

[Insert Table 6 – 7 around here]

4.2. Out-of-sample tests

Next, we investigate equity flows' out-of-sample forecasting ability from the two countries where equity flows could help to predict one-month-ahead returns (in-sample). Our motivation is that, firstly, a large number of studies suggest that there is no necessary association between in-sample and out-of-sample predictability (see, e.g., Welch and Goyal, 2007). Secondly, practitioners might be much more interested in out-of-sample forecasting.

To conduct our empirical analysis, we employ the standard out-of-sample R-squared to see whether predictive regression of equity flows could outperform a prevailing-mean model. Specifically, corresponding to each country, we first compute the one-month-ahead forecast using equity flows as a predictor. This takes the form as:

$$\hat{y}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t, \tag{7}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of intercept and slope coefficient (for equity flows), respectively. We use Newey-West robust standard errors to account for serial correlation and heteroscedasticity. For each out-of-sample evaluation, the data is collected from the start of the sample through month *t*. Next, we compare the one-month-ahead forecasted return $\hat{y}_{t:t+1}$ from the benchmark model (prevailing mean), which is calculated as the average excess returns from the beginning of the sample through month *t*. Formally, it can be written as below:

$$\hat{y}_{t+1} = average\ (\hat{y}_{1:t}), \tag{8}$$

In fact, the prevailing mean forecast is equivalent to the constant expected excess return model in Equation (7) with $\beta = 0$. If the benchmark model outperforms our predictive regression with equity flows, it would suggest that equity flows might not help to forecast future returns, such that it might be even better to calibrate returns time series with a random walk with drift. We compare the performance of these two models by comparing their Mean Squared Forecast Error (MSFE), which is also called as the out-of-sample R-squared statistics (Rapach et al., 2016). The period for out-of-sample evaluation is between January 2003 and December 2014. We use the statistics of Clark and West (2007) to test whether our predictive regression forecast delivers a significant improvement in MSFE. The null hypothesis of this test is that the benchmark (prevailing mean) MFSE is less than or equal to the predictive regression MSFE. This is corresponding to $H_0: R^2_{OS} \leq 0; H_1: R^2_{OS} > 0$, where R^2_{OS} represents the out-of-sample R-squared statistics (Rapach et al., 2016). If we could reject the null and accept the alternative hypothesis that the prevailing mean MFSE is greater than the predictive regression, then we can conclude that our predictive regression with equity flows as the regressor can outperform the benchmark model, thus international equity flows might contain relevant information to forecast future stock returns in EMEs.

[Insert Table 8 around here]

Table 8 shows our out-of-sample test results. In Column (1), we notice that the out-of-sample R-squared are almost all negative in all countries except Poland, which implies that equity flows to all these countries fail to outperform the prevailing mean benchmark model. In other words, equity flows to these countries might not be helpful to forecast future stock returns. Moreover, equity flows to South Africa lack significance in the out-of-sample test, even though the in-sample results are significant. Therefore, this observation confirms the conclusion of Welch and Goyal (2007) that in-sample predictability would not necessarily lead to out-of-sample forecasting ability, in which practitioners might be more interested. Finally, Poland seems to be the only remnant in our out-of-sample test. Yet, its significance is only at 10% level, even though its test statistics of Clark and West (2007) is close to 5% critical value. Overall, we find little evidence for the out-of-sample stock predictability of foreign investors in EMEs.

4.3. Trading strategies based on portfolio sorting

By focusing on the contemporaneous regressions, it would be useful to see whether the contemporaneous relation leads to a successful trading strategy. We sort the stock indices into 5 quintiles according to their (12-month, 26-month, and 60-month) rolling OLS betas on foreign equity flows and long each quintile with equal weights. Table 9 reports the results. The second column shows the mean of rolling OLS betas, while the last column shows the mean of number of EMEs in each quintile. Ret1, Ret12, Ret24, Ret36, Ret48 and Ret60 denote the cumulative buy-and-hold returns on a rolling window of 1, 12, 24, 36, 48 and 60 months ahead of the portfolio sorting month, respectively. Consistently with our intertemporal results, we could not find a pattern for any of the cumulative buy-and-hold returns at any horizons, no matter we use 12-month, 26-month, or 60-month rolling OLS betas on capital flows. We have also tried to repeat this exercise with the top and bottom 25% returns for each country, and the results are qualitatively similar. Overall, we find difficulty in building a profitable trading strategy based on past rolling OLS betas on foreign equity flows.

4.4. Average global equity flows and stock market returns in EMEs

Is there a way to capture the effect of the U.S. as a global leader in driving stock market returns in EMEs? In addition to individual equity flows, we look into the average global equity flow that may capture the effect of the U.S. (proxying a global factor). The results from this averaged scenario further confirms our results for each individual country in every table. We thank a referee for pointing it out. For a study of the effect of the U.S. stock market on international stock markets, see Rapach et al. (2013).

5. Concluding remarks

Global capital flows have significantly increased during the past two decades. Short-term capital flows, especially international equity flows, have a substantial impact on the stock markets in EMEs. Motivated by this conjecture, this paper seeks to investigate the interrelationship between international equity flows and the stock returns in EMEs.

To conduct our empirical analysis, we collect monthly data for 21 EMEs over 1995-2014. We employ both in-sample and out-of-sample tests to investigate our research question. As the exact degree of a predictor's persistence is not usually precisely identifiable, standard unit root test might not provide a firm guide (Lee, 2016). Therefore, we should employ predictive regressions, which could handle various degrees of persistence. To that end, this paper employs the state-of-art predictive regression models based on IVX-instrumentation, to ensure that our empirical results would not be a statistical artifact due to a persistent regressor.

One of our findings is a significant link between equity flows and contemporaneous stock returns among a large number of EMEs. This observation is especially prominent in Asian countries. Moreover, equity flows' estimated coefficients are mostly positive. All of these observations seem to confirm the immediate price impact of equity flows towards EMEs.

However, there is neither in-sample nor out-of-sample evidence that international equity flows could predict one-month-ahead stock returns. Among the a few countries where equity flows display significant estimates, their coefficients are negative and counter-intuitive. These observations imply that equity flows' price impact is not persistent: when equity flows rush into EMEs, they drive up prices contemporaneously but not persistently[12].

Our finding have important implications. Regarding flows equity flows, policymakers' attention should be more on their concurrent consequences than their future profitability. The remarkable turmoil in emerging stock markets during the GFC is a reminder of the importance of investigating their dynamics (e.g., Fuertes et al., 2016; Yan et al., 2016; Fuertes et al., 2017). We find difficulty in building a profitable trading strategy based on past rolling OLS betas on foreign equity flows.

There are some caveats to our investigation. Ideally, we should have considered other variables that may influence stock market returns. Additional variables include dividend yield and earning-price ratio (e.g., Rapach et al., 2016). However, the poor availability and quality of these fundamental variables for EMEs hinder our further investigation. We choose to avoid fundamentals in this study due to the poor quality of data in EMEs. We suspect that there might be a problem of misreporting, for we could observe a considerable amount of zero dividends for some countries. For example, Pakistan's dividends data start with January 1995, but it shows a series of zeros between November 1996 and May 1998—it might be unlikely for a whole nation to experience zero dividends for such a long time. For this reason, we use

[12] To some extent, the lack of out-of-sample predictability is to be expected as it is hard to predict stock returns (e.g., Welch and Goyal, 2009). However, it is a bit surprising that there is little in-sample evidence. We thank a referee for pointing it out.

data of prices only. We choose to focus on the EMEs in this paper, as they are still segregated from the developed markets, albeit the dramatic globalization over the past decades (e.g., Bekaert and Harvey, 2017). Our method can be used for other markets. Due to data limitation, we cannot rule out the possibility of predictability at a higher frequency in equity flows as well as other types of flows. Flows at higher frequency are more persistent, and there is a greater need for the tools we have introduced to this topic in this paper. We leave this work for future research.

6. Appendix.

This section discusses the potential problems associated with the traditional OLS approach. We first document the problem and present the solutions after that.

6.1. Statistical Inference in the Presence of Persistent Regressors

We start our analysis with ordinary least squares (OLS) regression, which is standard in the literature of predicting stock returns. The regression model is shown as:

$$y_t = \mu + Ax_{t-1} + \varepsilon_t \quad . \tag{A.1}$$

In this regression, y_t usually represents contemporaneous stock returns, and x_{t-1} denotes the lag of a vector of financial variables, which contains equity flows only in our case. A number of early findings based on such regressions report that the t-statistic is typically large enough to reject the null hypothesis that $A = 0$. Thus, they suggest a strong evidence of stock return predictability. However, Campbell and Yogo (2006) doubt the validity of such tests and further show that they tend to reject the null too frequently when the predictor variable is persistent and the innovations are highly correlated with returns.

Regarding the degrees of persistence of the predictor, we follow the presentations from Kostakis et al. (2015) and Lee (2016). We firstly assume that the vector of predictors x_{t-1} has the following autoregressive form:

$$x_t = R_n x_{t-1} + u_t, \tag{A.2}$$

$$R_n = I_K + \frac{C}{n^{\alpha}} \text{ for some } \alpha \geq 0 \quad , \tag{A.3}$$

where n is the sample size and $C = diag(c_1, c_2, c_3, \ldots., c_K)$ if we have K predictors. According to Equation (A.3), the pair (α, C) determines predictors' persistence. In particular, Lee (2016) shows that x_t can belong to any of the following persistence categories:

(I0) Stationary: $\alpha = 0$ and $|1 + c_i| < 1$, $\forall i$,

(MI) Mildly integrated: $\alpha \in (0,\ 1)\ and\ c_i \in (-\infty,\ 0)$, $\forall i$, (I1) Local to unity and unit root: $\alpha = 1$ and $c_i \in (-\infty, \infty)$, $\forall i$,

(ME) Mildly explosive: $\alpha \in (0,\ 1)$ and $c_i \in (0, \infty)$, $\forall i$.

If any predictor falls into the category of (I1) or even (ME), its persistence will lead to size distortion of the empirical results, as reported in the literature. On the other hand, Section 1 (Introduction) of this paper has briefly introduced the persistent nature of equity flows and the difficulty to identify the exact degree of their persistence empirically. Next, we show our solution by employing recent predictive regression based on IVX-filtering instrumentation.

6.2. Solutions: IVX filtering

The literature has developed two major approaches to correct the nonstandard distortion caused by persistent predictors. The first approach focuses on the Bonferroni method (e.g., Cavanagh et al., 1995; Campbell and Yogo, 2006). Its main idea is to find a confidence interval (CI) for R that incorporates confidence limits for c (shown in Equation A.3). In this way, the model can be independent of any particular value of c (Phillips, 2015). However, this method has several disadvantages: firstly, such models usually allow for only one predictor in the regression. More importantly, Phillips (2015) and Lee (2016) show that these models may lose validity when predictor persistence falls between (MI) and (I0). For this reason, it would be particularly difficult to employ models based on the Bonferroni method in our study, since it is empirically difficult to identify the exact degree of capital flows' persistence. Therefore, models retaining their validity over various degrees would be more desirable.

A solution to this problem is provided by the IVX filtering method of Phillips and Magdalinos (2009), which has been employed by recent studies such as Kostakis et al. (2015) and Lee (2016). These models can handle predictor variables with various degrees of persistence. The basic idea is to filter a predictor with strong persistence (e.g., belonging to the parameter space of I (1) into an instrument with mildly integrated (MI) persistence. Specifically, following the presentation from Lee (2016), we filter persistent data x_t to generate $\widetilde{z_t}$:

$$\widetilde{z_t} = F\widetilde{z_{t-1}} + \Delta x_t.$$

(A.4)

When $F = 0_K$, $\widetilde{z_t} = \Delta x_t$. In this case, the instrument $\widetilde{z_t}$ is equivalent to the first difference of the persistent predictor, which is one of the most common ways to remove persistence. Although first difference could wipe out the nonstandard distortion, its sacrifice is a substantial loss of power. On the other hand, when $F = I_K$ then $\widetilde{z_t} = x_t$, we simply use level data without any filtering. In this case, the power is retained, but the resulting persistence would lead to a distorted inference as we discussed earlier.

To exploit advantages both from using level and the first difference of persistent predictor, the IVX-method filters x_t to generate $\widetilde{z_t}$ with (MI) persistence, intermediate between I(0) and I(1). Specifically, we choose $F = R_{nz}$ so that:

$$\widetilde{z_t} = R_{nz}\widetilde{z_{t-1}} + \Delta x_t, \tag{A.5}$$

$$R_{nz} = I_K + \frac{C_z}{n^\delta}, \tag{A.6}$$

where $\delta \in (0,1)$, $C_z = c_z I_K$, $c_z < 0$ and $\widetilde{z_t} = 0$.

Equations (A.5) and (A.6) show several advantages of this method. Since R_{nz} is constructed to be between 0_K (first differencing) and I_K (use of level data), this IVX-filtering enables us to preserve power and achieve size correction at the same time. Another advantage is that this model could automatically adjust several persistent predictors simultaneously. Therefore, this method is even valid for regressions with multivariate predictors with various degrees of persistence. In this study, although we consider equity flow as the only predictor, the uniform validity over the range of I(0) and I(1) would still make this method attractive: if equity flow is I(1), the IVX filtering reduces the persistence to (MI); if equity flow belongs to I(0) or (MI), the filtering maintains the original persistence. Although equity flows might hardly be explosive, Phillips and Lee (2016) shows that models based on IVX instrumentation remain valid for regressors with local unit roots in the explosive direction and mildly explosive roots. In this way, this mechanism of self-generated instruments removes the worries of the unknown degree of capital flows' persistence.

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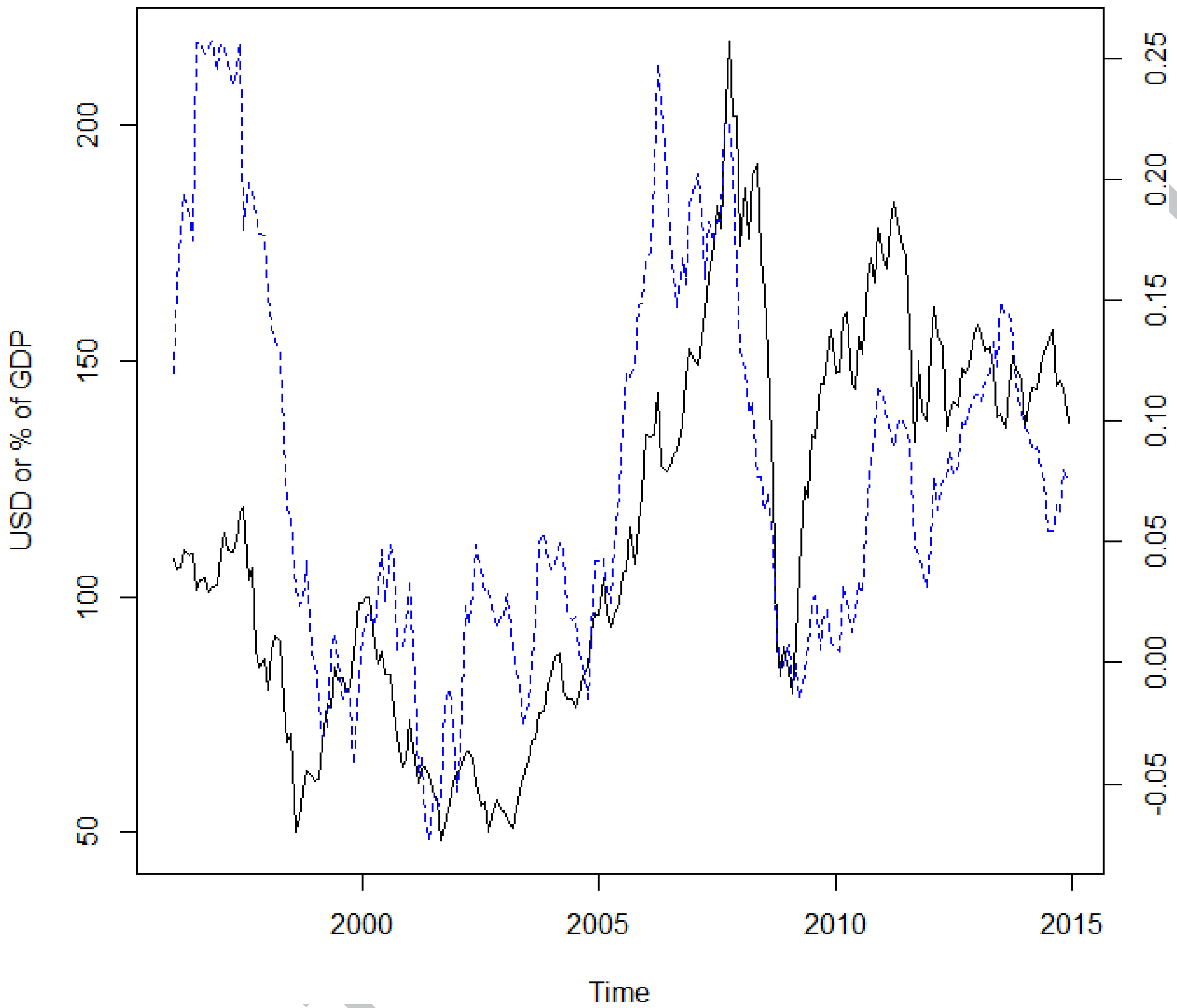

Figure 1. Stock Prices and International Equity Flows to EMEs. *1) Solid black line: real MSCI EME stock index. Left axis: in USD. 2) Dashed blue line: average equity flows to EMEs. Right axis: % of domestic GDP.*

Table 1. Summary Statistics. *This table reports the summary statistics of the key variables in this study. Mean and S.D. denote the mean value and standard deviation, respectively. Stock returns are computed from MSCI Index. Equity flows are in millions of USD.*

	Excess return		Gross flows		Gross flows (% gdp)	
Countries	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Asia						
China (PRC)	0.109	9.896	30.137	337.104	0.002	0.014
India	0.525	8.822	76.576	257.698	0.010	0.031
Indonesia	0.745	13.179	23.581	84.790	0.006	0.031
Malaysia	0.114	8.626	30.380	108.445	0.022	0.096
Pakistan	0.244	10.979	3.104	19.312	0.004	0.024
Philippines	0.006	8.629	9.100	31.519	0.010	0.034
Thailand	0.119	11.014	20.780	77.927	0.010	0.037
Latin America						
Argentina	0.604	11.498	1.857	137.226	0.001	0.048
Brazil	0.606	10.660	291.838	655.139	0.029	0.058
Chile	0.049	6.699	8.178	81.623	0.006	0.073
Colombia	0.642	9.086	5.300	60.974	0.003	0.034
Mexico	0.049	6.699	-35.686	253.960	-0.005	0.040
Peru	0.858	8.635	10.537	93.137	0.014	0.144
East EU						
Czech	0.498	8.279	-5.814	62.823	-0.007	0.099
Hungary	0.783	10.634	0.219	26.464	0.001	0.039
Poland	0.489	10.231	7.937	20.981	0.003	0.009
Russia	1.456	15.142	-1.178	73.542	0.000	0.012
Others						
Egypt	0.914	9.449	2.308	29.736	0.004	0.035
Morocco	0.157	5.484	0.350	3.372	0.001	0.007
Turkey	1.385	14.822	22.572	127.594	0.009	0.052
South Africa	0.288	7.680	29.356	104.053	0.017	0.060
Average	0.507	6.388	531.431	987.040	0.145	0.269

Table 2. Gross flows and contemporaneous stock returns. *Stock returns are computed from MSCI Index. Equity flows are in millions of USD. Panel C reports the results of estimated coefficients. Light and dark gray denote 10% and 5% significance level, respectively*.

	Panel A: OLS			Panel B: IVX-Wald			Panel C: IVX-QR				
Countries	**Coef**	**T-stat**	**P-value**	**Coef**	**IVX_Wald**	**P-value**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Asia											
China	0.000	-0.172	0.864	0.000	0.024	0.876	0.001	-0.001	-0.001	-0.001	0.004
India	0.007	3.400	0.001	0.007	11.393	0.001	0.010	0.009	0.007	0.002	0.005
Indonesia	0.011	1.307	0.193	0.012	1.336	0.248	0.029	0.034	0.015	0.000	0.010
Malaysia	0.015	4.035	0.000	0.015	9.124	0.003	0.018	0.015	0.010	0.015	0.016
Pakistan	0.021	0.793	0.428	0.023	0.372	0.542	0.067	0.011	0.027	0.043	-0.068
Philippines	0.058	3.706	0.000	0.061	12.140	0.000	0.062	0.062	0.048	0.043	0.063
Thailand	0.025	3.642	0.000	0.024	6.922	0.009	0.018	0.026	0.030	0.024	0.004
Latin America											
Argentina	0.000	-0.113	0.910	0.000	0.000	0.995	0.000	0.001	-0.001	-0.001	-0.010
Brazil	0.003	3.032	0.003	0.003	9.141	0.002	0.004	0.003	0.002	0.005	0.005
Chile	-0.008	-1.498	0.135	-0.008	2.293	0.130	-0.019	-0.015	-0.004	-0.002	-0.005
Colombia	-0.003	-0.327	0.744	-0.003	0.068	0.795	0.001	-0.009	0.008	0.003	-0.013
Mexico	0.003	1.587	0.114	0.003	2.667	0.102	0.004	0.002	0.001	0.003	0.001
Peru	0.007	1.205	0.229	0.007	1.232	0.267	0.012	0.006	0.003	0.018	0.024
East EU											
Czech	0.021	3.124	0.002	0.021	6.087	0.014	0.015	0.013	0.018	0.026	0.034
Hungary	0.007	0.374	0.709	0.014	0.298	0.585	0.021	0.010	-0.028	0.005	-0.012
Poland	0.005	0.176	0.860	0.008	0.057	0.811	0.037	0.029	0.008	0.061	-0.031
Russia	0.034	3.022	0.003	0.034	6.697	0.010	0.023	0.034	0.028	0.031	0.040
Others											
Egypt	0.032	1.794	0.074	0.033	2.549	0.110	0.054	0.055	0.042	0.018	-0.008
Morocco	0.200	1.626	0.105	0.204	3.783	0.052	0.069	0.137	0.213	0.305	0.239
Turkey	0.011	1.182	0.239	0.011	2.041	0.153	0.001	0.009	0.006	0.007	0.023
South Africa	0.010	2.397	0.017	0.010	3.965	0.046	0.014	0.007	0.003	0.008	0.014
Average	0.002	5.550	0.000	0.003	41.086	0.000	0.003	0.003	0.003	0.002	0.002

Table 3. Gross flows and one-month-ahead stock returns. *Stock returns are computed from MSCI Index. Equity flows are in millions of USD. Panel C reports the results of estimated coefficients. Light and dark gray denote 10% and 5% significance level, respectively*.

	Panel A: OLS			Panel B: IVX-Wald			Panel C: IVX-QR				
Countries	**Coef**	**T-stat**	**P-value**	**Coef**	**IVX_Wald**	**P-value**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Asia											
China	-0.002	-1.151	0.251	-0.002	0.998	0.318	-0.002	-0.004	-0.003	-0.001	-0.001
India	-0.001	-0.564	0.573	-0.001	0.209	0.648	0.006	0.003	-0.002	-0.005	-0.005
Indonesia	0.004	0.597	0.551	0.004	0.194	0.660	0.020	0.004	0.006	0.003	-0.026
Malaysia	0.005	1.270	0.205	0.005	0.856	0.355	0.011	0.006	0.005	0.002	0.000
Pakistan	-0.001	-0.033	0.974	0.000	0.000	0.999	0.052	0.008	-0.007	0.019	-0.080
Philippines	0.000	0.023	0.982	0.003	0.023	0.878	0.020	0.009	0.022	0.029	-0.005
Thailand	0.002	0.210	0.834	0.001	0.005	0.945	0.002	0.000	-0.006	0.011	-0.009
Latin America											
Argentina	-0.003	-0.742	0.459	-0.002	0.207	0.649	0.000	0.001	-0.004	-0.007	0.010
Brazil	0.000	0.324	0.746	0.000	0.145	0.703	0.003	0.001	0.000	0.000	-0.001
Chile	-0.006	-0.915	0.361	-0.006	1.185	0.276	-0.020	-0.004	-0.007	0.004	0.001
Colombia	-0.012	-1.960	0.051	-0.012	1.439	0.230	-0.003	-0.018	-0.011	0.011	-0.026
Mexico	0.002	1.231	0.220	0.002	1.032	0.310	0.002	0.003	0.001	0.003	0.001
Peru	0.001	0.505	0.614	0.002	0.069	0.793	0.008	0.006	0.002	-0.004	-0.009
East EU											
Czech	0.002	0.274	0.784	0.002	0.081	0.776	0.008	-0.005	0.003	-0.003	-0.012
Hungary	0.018	0.640	0.523	0.018	0.478	0.489	-0.024	0.011	0.030	0.042	0.051
Poland	-0.068	-2.173	0.031	-0.067	4.528	0.033	-0.049	-0.042	-0.059	-0.055	-0.054
Russia	0.010	0.957	0.339	0.011	0.678	0.410	0.043	0.020	0.002	0.005	0.008
Others											
Egypt	0.029	1.020	0.309	0.030	2.189	0.139	0.037	0.018	0.032	-0.005	-0.002
Morocco	0.124	1.076	0.283	0.128	1.477	0.224	0.086	0.099	0.034	0.160	0.101
Turkey	-0.012	-1.626	0.105	-0.012	2.505	0.113	-0.002	-0.007	-0.016	-0.010	-0.014
South Africa	-0.011	-2.012	0.045	-0.011	4.892	0.027	-0.008	-0.015	-0.019	-0.006	-0.013
Average	0.000	-0.616	0.538	0.000	0.240	0.624	-0.002	-0.001	0.001	0.000	-0.001

Table 4. Net flows and contemporaneous stock returns. *Stock returns are computed from MSCI Index. Equity flows are in millions of USD. Panel C reports the results of estimated coefficients. Light and dark gray denote 10% and 5% significance level, respectively*.

	Panel A: OLS			Panel B: IVX-Wald			Panel C: IVX-QR				
Countries	**Coef**	**T-stat**	**P-value**	**Coef**	**IVX_Wald**	**P-value**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Asia											
China	0.000	-0.269	0.788	0.000	0.046	0.830	0.001	0.002	0.000	-0.001	0.000
India	0.007	4.156	0.000	0.007	14.019	0.000	0.010	0.009	0.008	0.004	0.005
Indonesia	0.010	1.204	0.230	0.010	1.101	0.294	0.030	0.034	0.015	0.000	-0.007
Malaysia	0.009	3.179	0.002	0.009	4.241	0.039	0.015	0.010	0.006	0.004	0.010
Pakistan	0.023	0.870	0.385	0.026	0.515	0.473	0.067	0.011	0.026	0.035	-0.071
Philippines	0.056	4.118	0.000	0.060	15.314	0.000	0.068	0.056	0.041	0.046	0.080
Thailand	0.021	3.075	0.002	0.020	5.054	0.025	0.013	0.021	0.028	0.028	-0.003
Latin America											
Argentina	-0.005	-0.881	0.379	-0.005	0.847	0.357	0.000	0.001	-0.004	-0.001	-0.007
Brazil	0.003	3.140	0.002	0.003	9.531	0.002	0.004	0.003	0.002	0.005	0.005
Chile	-0.002	-0.992	0.322	-0.002	0.550	0.458	0.002	0.000	0.001	0.003	0.001
Colombia	0.004	0.594	0.553	0.003	0.182	0.669	0.001	-0.002	0.008	0.006	0.013
Mexico	0.000	-0.144	0.886	0.000	0.003	0.953	-0.002	-0.001	0.000	0.002	0.001
Peru	0.004	0.944	0.346	0.005	0.873	0.350	0.009	0.006	0.002	0.000	0.012
East EU											
Czech	0.016	2.172	0.031	0.016	3.835	0.050	0.009	0.012	0.018	0.022	0.034
Hungary	-0.020	-1.202	0.231	-0.017	0.871	0.351	-0.031	-0.027	-0.031	0.004	-0.012
Poland	-0.012	-0.500	0.618	-0.011	0.182	0.670	0.031	0.021	-0.025	-0.021	-0.054
Russia	0.034	3.012	0.003	0.033	6.496	0.011	0.021	0.040	0.029	0.030	0.041
Others											
Egypt	0.027	1.439	0.152	0.028	2.244	0.134	0.053	0.058	0.042	0.019	-0.008
Morocco	-0.018	-0.507	0.613	-0.015	0.108	0.743	0.054	0.020	-0.031	-0.024	0.009
Turkey	0.011	1.212	0.227	0.011	2.183	0.139	0.012	0.008	0.005	0.007	0.024
South Africa	0.012	2.792	0.006	0.012	8.028	0.005	0.014	0.007	0.002	0.009	0.016
Average	0.002	5.897	0.000	0.002	34.691	0.000	0.003	0.002	0.002	0.002	0.002

Table 5. Net flows and one-month-ahead stock returns. *Stock returns are computed from MSCI Index. Equity flows are in millions of USD. Panel C reports the results of estimated coefficients. Light and dark gray denote 10% and 5% significance level, respectively*.

	Panel A: OLS			Panel B: IVX-Wald			Panel C: IVX-QR				
Countries	**Coef**	**T-stat**	**P-value**	**Coef**	**IVX_Wald**	**P-value**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Asia											
China	-0.002	-1.522	0.129	-0.002	1.602	0.206	-0.002	-0.003	-0.003	-0.001	-0.004
India	-0.001	-0.545	0.586	-0.001	0.194	0.659	0.006	0.001	-0.002	-0.004	-0.005
Indonesia	0.004	0.626	0.532	0.005	0.212	0.645	0.017	0.003	0.005	0.006	-0.025
Malaysia	0.005	1.613	0.108	0.005	1.166	0.280	0.007	0.000	0.003	0.000	0.001
Pakistan	0.012	0.340	0.734	0.013	0.126	0.722	0.082	0.007	0.023	0.026	-0.064
Philippines	0.009	0.556	0.579	0.010	0.385	0.535	0.017	0.009	0.024	0.034	-0.004
Thailand	0.001	0.175	0.861	0.000	0.001	0.975	0.002	0.001	0.006	0.009	-0.009
Latin America											
Argentina	0.000	0.092	0.927	0.001	0.013	0.909	0.007	0.001	-0.004	-0.007	0.005
Brazil	0.001	0.741	0.459	0.001	0.434	0.510	0.002	0.001	0.001	0.000	-0.001
Chile	0.001	0.571	0.569	0.001	0.420	0.517	-0.001	-0.003	0.004	0.006	0.001
Colombia	-0.006	-0.922	0.357	-0.005	0.472	0.492	-0.010	0.000	-0.005	0.008	0.003
Mexico	0.002	1.256	0.210	0.002	1.562	0.211	0.000	0.002	0.001	0.003	0.002
Peru	0.005	1.770	0.078	0.005	1.049	0.306	0.009	0.009	0.002	0.009	0.013
East EU											
Czech	0.002	0.252	0.802	0.002	0.063	0.802	0.007	-0.003	0.003	-0.003	-0.018
Hungary	-0.006	-0.300	0.765	-0.007	0.139	0.709	0.019	-0.002	-0.012	-0.021	0.000
Poland	-0.041	-1.668	0.097	-0.040	2.431	0.119	-0.038	-0.023	-0.049	-0.051	-0.034
Russia	0.011	1.041	0.299	0.013	1.012	0.314	0.043	0.021	0.002	0.005	0.008
Others											
Egypt	0.039	1.557	0.121	0.039	4.418	0.036	0.037	0.024	0.028	0.017	0.021
Morocco	0.033	1.078	0.282	0.035	0.602	0.438	0.007	-0.014	0.029	0.039	0.073
Turkey	-0.012	-1.602	0.110	-0.012	2.456	0.117	-0.001	-0.007	-0.015	-0.009	-0.014
South Africa	-0.005	-0.804	0.422	-0.005	1.243	0.265	0.000	-0.004	0.001	-0.004	-0.012
Average	0.000	0.155	0.877	0.000	0.047	0.829	0.000	0.000	0.000	0.000	0.000

Table 6. GDP scaled gross flows and contemporaneous stock returns. *Stock returns are computed from MSCI Index. Equity flows are in millions of USD. Panel C reports the results of estimated coefficients. Light and dark gray denote 10% and 5% significance level, respectively.*

	Panel A: OLS			Panel B: IVX-Wald			Panel C: IVX-QR				
Countries	**Coef**	**T-stat**	**P-value**	**Coef**	**IVX_Wald**	**P-value**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Asia											
China	42.624	1.346	0.180	40.345	0.761	0.383	52.218	36.634	13.265	-13.901	71.305
India	63.860	3.378	0.001	63.423	12.264	0.000	72.142	76.869	51.610	14.484	34.440
Indonesia	33.675	0.997	0.320	33.247	1.406	0.236	56.218	68.258	44.751	20.515	46.547
Malaysia	17.732	3.203	0.002	18.336	10.304	0.001	21.521	18.455	19.756	22.103	23.074
Pakistan	7.755	0.403	0.688	9.008	0.094	0.760	39.754	6.267	6.251	9.300	-53.324
Philippines	53.818	3.763	0.000	58.167	13.016	0.000	52.544	59.270	41.405	47.974	67.395
Thailand	63.148	4.723	0.000	61.406	10.588	0.001	44.667	58.957	78.875	64.050	5.399
Latin America											
Argentina	1.160	0.103	0.918	2.267	0.022	0.883	-0.634	1.758	14.716	-3.085	-27.285
Brazil	43.642	3.471	0.001	44.969	14.740	0.000	46.291	58.262	28.552	45.781	40.035
Chile	-5.563	-0.995	0.321	-5.780	0.927	0.336	-23.101	-13.575	-0.894	-2.517	-8.083
Colombia	-0.034	-0.002	0.998	0.855	0.002	0.960	1.844	-8.976	9.045	4.246	-15.000
Mexico	20.569	1.986	0.048	22.968	4.367	0.037	24.632	17.208	20.915	18.498	15.362
Peru	4.879	1.223	0.223	4.929	1.620	0.203	5.953	2.824	2.484	15.633	22.491
East EU											
Czech	10.330	2.512	0.013	10.592	3.856	0.050	2.103	6.669	9.728	13.882	18.141
Hungary	3.075	0.255	0.799	11.152	0.367	0.545	12.579	4.895	-12.851	4.557	-11.278
Poland	62.229	0.961	0.338	66.165	0.810	0.368	118.835	83.418	37.521	157.506	-82.820
Russia	157.611	2.259	0.025	155.371	3.976	0.046	121.942	78.791	158.155	164.143	216.660
Others											
Egypt	23.905	1.671	0.096	24.331	1.971	0.160	24.638	60.747	32.933	15.091	-5.319
Morocco	119.619	2.256	0.025	120.789	6.069	0.014	42.971	103.050	108.598	167.081	137.841
Turkey	28.512	1.213	0.226	28.694	2.388	0.122	2.171	12.599	23.186	15.370	49.991
South Africa	15.892	2.478	0.014	15.755	3.660	0.056	27.234	13.613	5.550	17.169	21.971
Average	9.632	6.197	0.000	9.753	47.415	0.000	13.452	12.040	9.112	6.673	8.063

Table 7. GDP scaled gross flows and one-month-ahead stock returns. *Stock returns are computed from MSCI Index. Equity flows are in millions of USD. Panel C reports the results of estimated coefficients. Light and dark gray denote 10% and 5% significance level, respectively.*

	Panel A: OLS			Panel B: IVX-Wald			Panel C: IVX-QR				
Countries	**Coef**	**T-stat**	**P-value**	**Coef**	**IVX_Wald**	**P-value**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
Asia											
China	-6.494	-0.169	0.866	-7.999	0.030	0.863	-69.963	-17.608	-55.372	-9.619	-65.728
India	-15.941	-0.934	0.351	-14.864	0.642	0.423	-23.921	-23.526	-20.250	-28.057	-8.270
Indonesia	35.042	1.243	0.215	35.206	1.590	0.207	40.424	52.704	43.730	18.400	95.673
Malaysia	5.507	1.167	0.244	5.029	0.725	0.394	14.163	-0.682	-0.547	2.571	-0.345
Pakistan	-1.158	-0.044	0.965	-0.584	0.000	0.984	54.803	8.608	-4.523	7.808	-67.166
Philippines	-0.451	-0.021	0.983	2.590	0.025	0.875	22.934	29.354	26.392	34.036	-5.013
Thailand	8.563	0.499	0.618	5.469	0.080	0.777	7.697	5.613	-9.412	25.935	2.003
Latin America											
Argentina	-4.924	-0.429	0.668	-4.333	0.080	0.778	1.228	2.394	-11.841	-3.322	36.293
Brazil	5.191	0.578	0.564	7.114	0.346	0.556	38.902	12.252	-0.572	1.789	-10.649
Chile	-7.386	-1.153	0.250	-7.242	1.478	0.224	-1.427	-3.120	-6.431	2.903	0.467
Colombia	-22.081	-2.006	0.046	-20.799	1.476	0.224	-3.785	-25.959	-24.742	10.766	-43.607
Mexico	11.582	1.240	0.216	11.149	1.079	0.299	15.210	17.890	6.909	17.943	8.055
Peru	1.253	0.808	0.420	1.339	0.119	0.730	5.542	3.314	0.961	3.499	-4.613
East EU											
Czech	2.441	0.486	0.627	2.689	0.245	0.620	4.314	-2.818	1.807	5.757	10.248
Hungary	25.099	1.347	0.179	25.496	2.093	0.148	19.527	10.102	39.373	48.954	37.097
Poland	-119.970	-1.834	0.068	-117.357	2.566	0.109	-139.538	-38.397	-127.668	-75.602	-157.820
Russia	5.434	0.088	0.930	10.519	0.018	0.894	176.687	22.371	9.926	-14.818	9.296
Others											
Egypt	32.353	1.157	0.248	33.286	3.728	0.054	30.423	13.256	23.824	14.977	19.617
Morocco	63.473	1.217	0.225	64.764	1.715	0.190	63.300	32.764	20.903	68.062	56.971
Turkey	-33.496	-1.721	0.086	-33.489	3.281	0.070	-14.699	-19.966	-31.902	-41.782	-32.067
South Africa	-21.490	-2.357	0.019	-21.617	6.967	0.008	-15.936	-28.509	-25.055	-12.671	-24.976
South Africa	-0.879	-0.573	0.567	-0.770	0.237	0.627	-1.500	-1.472	2.064	1.470	-3.733

Table 8. Out-of-sample test results (2003:12-2014:12). *This table reports the out-of-sample (oos) R-squared in the first column. The second column shows the test statistics of Clark and West (2007), where the null hypothesis is that the predictive regression cannot outperform the benchmark (prevailing mean) model. Light and dark gray denote 10% and 5% significance level, respectively.*

	Gross flows oos		Net flows oos		Gross flows (% gdp) oos	
Countries	**OS_R2**	**CW stats**	**OS_R2**	**CW stats**	**OS_R2**	**CW stats**
Asia						
China	-15.129	0.575	-6.231	0.643	-9.774	0.372
India	-5.963	0.415	-5.924	0.434	-3.643	0.674
Indonesia	-6.622	-1.192	-6.273	-1.178	-7.805	-1.047
Malaysia	-0.296	0.786	-2.207	0.929	0.289	0.707
Pakistan	-1.258	-1.111	-1.066	-0.287	-0.586	-1.533
Philippines	-0.927	-0.925	-0.541	0.117	-0.533	-1.181
Thailand	-10.635	-0.953	-10.250	-1.099	-10.088	-1.065
Latin America						
Argentina	-0.193	0.052	-2.706	-0.508	-0.346	-0.198
Brazil	-1.507	-2.499	-1.223	-1.105	-0.635	-0.825
Chile	-1.663	-0.123	-2.601	-0.793	-0.487	0.314
Colombia	-0.598	0.457	-3.412	-0.269	0.263	0.808
Mexico	-0.944	-0.414	-1.516	-0.283	-0.706	-0.244
Peru	-0.164	-0.359	0.329	1.173	0.025	0.243
East EU						
Czech	-0.402	-0.304	-0.407	-0.426	-0.046	-0.093
Hungary	-5.320	-0.797	-8.591	-1.497	-2.468	-0.682
Poland	2.448	1.640	0.582	0.889	1.649	1.658
Russia	-1.832	-0.161	-0.787	-0.394	-1.944	-0.728
Others						
Egypt	-8.326	0.440	-2.637	1.145	-7.261	0.385
Morocco	-1.779	-0.266	-1.249	1.105	-0.809	-0.004
Turkey	-1.979	0.360	-2.353	0.154	-0.647	0.330
South Africa	-3.725	0.324	-3.565	-0.353	-1.291	0.508
Average	-1.754	-1.164	-2.296	-0.689	-0.839	-0.972

Table 9. Trading strategies based on portfolio sorting. *This table reports results when we sort the stock indices into 5 quintiles according to their (12-month, 26-month, and 60-month) rolling OLS betas on foreign equity flows and long each quintile with equal weights. The second column shows the mean of rolling OLS betas, while the last column shows the mean of number of EMEs in each quintile. Ret1, Ret12, Ret24, Ret36, Ret48 and Ret60 denote the cumulative buy-and-hold returns on a rolling window of 1, 12, 24, 36, 48 and 60 months ahead of the portfolio sorting month, respectively.*

Quintile	Betas	Ret1	Ret12	Ret24	Ret36	Ret48	Ret60	Obs
Panel A: 12-month rolling betas								
1	-0.203	1.094	9.249	15.122	22.119	29.151	38.316	4.0
2	-0.009	0.574	5.563	11.022	17.405	23.574	30.106	4.0
3	0.024	0.216	4.143	8.176	15.299	21.789	27.944	4.0
4	0.080	0.545	4.584	10.035	18.214	25.669	30.677	4.0
5	0.344	0.226	6.417	12.629	20.514	26.603	32.415	5.0
Average	0.047	0.531	5.991	11.397	18.710	25.357	31.892	4.2
Panel B: 36-month rolling betas								
1	-0.049	0.464	8.527	15.579	23.330	33.190	41.271	4.0
2	0.004	0.675	7.107	13.197	19.553	27.304	36.127	4.0
3	0.018	0.910	8.908	16.225	23.991	33.146	42.474	4.0
4	0.045	0.858	9.373	17.477	22.676	30.897	39.683	4.0
5	0.182	0.358	7.344	15.586	24.457	34.310	44.566	5.0
Average	0.040	0.653	8.252	15.613	22.801	31.769	40.824	4.2
Panel C: 60-month rolling betas								
1	-0.026	0.408	7.936	18.140	27.602	33.713	38.916	4.0
2	0.006	0.656	9.656	20.785	31.139	40.035	43.688	4.0
3	0.016	0.547	6.812	16.723	26.841	35.987	41.856	4.0
4	0.034	0.664	8.249	16.935	27.199	37.503	45.930	4.0
5	0.142	0.557	8.500	19.474	30.717	40.075	47.515	5.0
Average	0.035	0.566	8.231	18.411	28.699	37.463	43.581	4.2

HIGHLIGHTS

- Compare IVX-Wald and IVX-Quantile regression with OLS.
- Examining the stock return predictability in emerging markets.
- Robust positive contemporaneous relationship flows and returns.
- Little evidence between flows and one-month-ahead returns.