Cross-Border Capital Flows and Return Dynamics in Emerging Stock Markets: Relative Roles of Equity and Debt Flows[#]

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Abstract

This paper examines the effect of cross-border capital flows on financial markets by focusing on the composition of flows, viz. equity and debt flows, and its relative effect on emerging stock market returns and volatility. Using a panel GARCH approach on nine emerging market economies, we find that both equity and debt flows possess incremental information over stock market returns and volatility that is not captured by aggregate capital market risk factors. While the explanatory power of debt flows is relatively stronger and more robust, even after controlling for world market return, global risk, bank credit flows and country-level liquidity, we find that equity flows assume significant explanatory power, particularly during the post-global financial crisis period. The findings overall suggest that emerging stock markets have become particularly sensitive to cross-border capital flows following the great credit crunch, with significant effects on idiosyncratic risks at the country level, while accounting for the composition of portfolio flows can add further explanatory power to stock market models.

Keywords: Cross-border portfolio flows, emerging stock markets, panel GARCH.
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1. Introduction

Globalization and financial integration is a double-edged sword, particularly for emerging markets. While capital flows into emerging market economies can be a blessing, helping to prop up currency values and investor sentiment in local financial markets, they can also lead to disastrous outcomes, especially when fragile economies are exposed to hot money flows. Clearly, rising financial integration has resulted in an increase in cross-border capital flows that have played an increasing role in driving return dynamics in emerging stock markets (e.g. Henry, 1998 and Bekaert et al., 2002). In a recent study, Rey (2018) argues the presence of a global financial cycle in capital flows and shows that asset markets with more credit inflows are more sensitive to the global cycle. This finding complements earlier evidence that stock prices and gross capital flows respond to a common global factor (Passari and Rey, 2015; Miranda-Agrippino and Rey, 2020), establishing a link between capital flows and stock valuations in global financial markets (e.g. Nier et al., 2014, Anaya et al., 2017).[1]

Despite the multitude of studies on the effect of cross-border capital flows on financial market returns, very few studies, however, have focused on the composition of flows, viz. equity and debt flows, and its relative effect on equity returns. Earlier studies including Taylor and Sarno (1997) and Chuhan et al. (1998) note that equity and bond flows exhibit heterogeneous patterns in terms of their sensitivity to global and domestic factors, while Krugman (2000) highlights the importance of debt flows as they are more likely to exacerbate cycles in asset prices and can encourage risky lending during economic booms. Examining the transmission of the U.S. financial crisis to equity markets worldwide, Yan et al., (2016) find that crisis is mostly transmitted through bank credit rather than portfolio flows and international trade. Against this backdrop, our work

[1] See Gourinchas and Rey (2014) for a review.

extends the strand of literature that evaluates the significance of capital flows in driving emerging market returns from a novel perspective by distinguishing between equity and debt flows for nine emerging market economies (EMEs) and examining the effect of capital flows on stock market return, volatility as well as idiosyncratic risks via the parametric panel data framework proposed by Cermeño and Grier (2006). Considering that policymakers are always concerned about the size and permanence of cross-border capital flows, the analysis is of interest from a policy perspective in addition to its investment implications for the pricing of emerging market assets and their risk exposures with respect to global risk factors.

The empirical literature concerning the role of capital flows has focused mainly on determining the drivers of capital flows, 'push' v/s 'pull' factors (e.g. Fratzscher, 2012; Ahmed and Zlate, 2014). In this strand of the literature, a growing number of studies argue that U.S. monetary policy serves as a major driver of capital flows to emerging markets (e.g. Taylor and Samo, 1997; De Vita and Kyaw 2008; Bluedorn et al. 2013). This is widely termed as "push" factors in which monetary and fiscal policy decisions in developed markets drive the push in capital flows to emerging economies. Other studies, however, place a greater role on "pull" factors, arguing that the economic and financial developments in emerging markets matter more in attracting foreign capital (e.g. Ghosh and Ostry, 1993; Chuhan et al. 1998). In line with this argument, Ahmed and Zlate (2014) explore the determinants of private capital flows to EMEs and observe that growth and interest rate differentials between EMEs and advanced economies as well as global risk appetite are statistically and economically significant determinants of net private capital inflows.

Regardless of the nature of the driving factors for international capital flows, numerous studies document that the recipient of capital flows experience both potential benefits (investment and growth) and costs regarding financial stability and risks associated with capital reversals (e.g. Prasad et al. 2003; Henry, 2006).[2] Accordingly, given the significant structural changes in the conduct of monetary and fiscal policies as a response to the 2007/2008 financial crisis and the evidence that equity and debt flows differ in their sensitivity to global and domestic factors, an interesting research question is whether the composition of cross-border capital flows plays a role in deterimining risk and return dynamics in emerging financial markets even after controlling for aggregate and market specific effects and whether or not a possible capital flow effect on EMEs has experienced a structural change following the global financial crisis.[3]

Empirical studies on EMEs generally find that net capital flows are volatile, pro-cyclical and decline during crisis periods (e.g. Dornbusch et al., 1995; Broner and Rigobon, 2006 and Mendoza, 2010), while Broner et al. (2013) show that the same result holds for gross capital flows as well.[4] In earlier studies, Bohn and Tesar (1996) and Brennan and Cao (1997) examine the relationship between aggregate investor purchases in major capital markets and asset returns and find evidence of a positive and contemporaneous correlation between inflows and asset returns. Similarly, using binary VAR framework, Froot et al. (2001) examine the behaviour of portfolio equity flows and its conditional relationship with local asset returns, documenting positive, contemporaneous covariance between net inflows and equity as well as currency returns. However, these studies focus on equity market related purchases and sales, without jointly examining capital flows across equity and bond markets. Accordingly, the literature provides limited evidence on the

[2]For example, Chari and Henry (2004) show that an increase in foreign portfolio flows results in a decrease in local systematic risk, while Kim and Singal (2000) show that an increase in equity flows are associated with a decrease in domestic cost of capital. .

[3] Previous studies, including Dahlhaus and Vasishtha (2014) and World Bank (2014), find that the U.S. Fed policy expectations as well as the Fed's quantitative easing programs have had a significant impact on capital flows to emerging markets.

[4] Gross capital flows include capital inflows by foreign agents as well as capital outflows by domestic agents.

dynamics of equity and debt flows separately and their relative roles as a driver of financial returns in EMEs.

Our work falls in the strand of literature that evaluates the significance of capital flows as a driver of emerging market returns. Specifically, we utilize country-level equity (debt) flow data, measured by net non-resident purchases of common stocks (bonds), for nine EMEs including Brazil, Bulgaria, Chile, Czech Republic, India, Indonesia, Korea, Poland and South Africa and analyze the relative roles of equity and debt flows as a determinant of risk and return dynamics in these markets. From a methodological perspective, the panel GARCH methodology adopted in our empirical analysis provides several advantages when compared with the conventional, OLS-based time-series or cross-sectional models that are generally utilized in the literature. First, conditional mean models with GARCH type errors provide a more efficient estimation method under conditional heteroskedasticity, which may lead to misleading inferences if conditional heteroskedasticity effects are present and left unaccounted for when OLS is adopted. Second, time-series based models ignore, by construction, the presence of possible cross-sectional interdependencies which can be addressed in a panel setting. This is an important consideration given the evidence that stock return volatilities exhibit co-behavioral patterns over time and across markets. The panel GARCH approach we employ overcomes these shortfalls by taking into account both cross-sectional interdependencies and individual heterogeneity across cross-sectional units. Finally, since the dynamic panel GARCH framework directly specifies the conditional mean and the conditional variance-covariance matrix of stock market returns, it can be used to simultaneously test the impact of portfolio flows on both the first and second moments of the stock returns.

Our findings suggest that fund flows (both equity and debt) possess incremental information over emerging stock market returns and volatility that is not captured by aggregate capital market factors. The explanatory power of debt flows is relatively stronger than that of equity flows, both for stock market returns and volatility and is robust to the inclusion of a number of control variables including world market return, global risk, bank credit flows, market liquidity as well as leverage effects. Considering that bond flows, compared to equity flows, are more sensitive to a country's credit rating than global factors (Chuhan et al., 1998) and the recent evidence that establishes a link between credit rating announcements for EMEs and stock market volatility (Balcilar et al., 2017), our findings suggest that the effect of bond flows on stock market volatility reflects market sentiment around credit ratings announcements, which cannot be captured by equity flows.

At the same time, we find that equity flows assume significant explanatory power, particularly during the post-global financial crisis period, even absorbing some of the explanatory power of aggregate capital market movements during the post-crisis era. The findings overall suggest that emerging stock markets have become particularly sensitive to fund flows following the great credit crunch, with significant wealth and risk effects, while accounting for the composition of portfolio flows can add further explanatory power to stock market models. Additional tests further show that changes in debt flows can serve as a significant determinant of crash risks in emerging stock markets, which is an important consideration given the evidence of co-dependencies at extreme quantiles of the conditional distribution of financial returns across global markets.

Finally, our findings indicate a significant effect of debt flows on idiosyncratic risks at the country level, while the effect of equity flows is rather limited to the measure of idiosyncratic volatility used in the analysis. From an economic perspective, the findings suggest that net capital flows to emerging stock markets, particularly debt flows, have significant wealth and risk effects, while they can help lower country-specific risks. This is an important consideration when it comes to the estimation of risk premia associated with emerging market valuations and the cost of capital estimations for capital budgeting decisions. The remainder of the paper is structured as follows. Section 2 describes the data and econometric model. Section 3 presents the empirical findings, and Section 4 concludes.

2. Data and Methodology

2.1. Data

The dataset used in our empirical analysis includes monthly portfolio flows for nine emerging markets including Brazil, Bulgaria, Chile, Czech Republic, India, Indonesia, Korea, Poland and South Africa, obtained from the International Institute of Finance for the period January 2005 to March 2017.[5] The equity (bond) flows for a given country are measured by net non-resident purchases of common stocks (bonds). In order to allow for a fair comparison across countries, the flow data for each country are standardized using the GDP value. The data for country stock market indexes are obtained from Thomson Eikon. Stock returns are computed as the logarithmic first difference of the stock price, that is $R_{i,t} = \log\left(P_{i,t} / P_{i,t-1}\right) * 100$, $i = 1,...,N$, $t = 1,..,T$, where $P_{i,t}$ denotes the stock market index value of country *i* at time period *t*.

Figures 1-3 present the plots for monthly equity and debt flows, and Figure 4 presents the plots for stock market returns. As can be seen in Figures 1-3, emerging market economies (e.g.

[5] The panel GARCH methodology requires a balanced panel for both equity and debt flows. Given this mandate and based on the data availability, our final sample includes nine EMEs.

Brazil, India) generally enjoyed positive equity inflows in the aftermath of the global financial crisis of 2007-08, likely due to the implementation of accommodative monetary policy by advanced economies. We observe that Asian and Latin American economies in particular, received a significant proportion of both equity and debt flows, while India seems to stand out with a notable rise in both equity and debt flows in recent periods. In the case of the emerging European economies, however, we observe generally negative debt flows, particularly for Poland and the Czech Republic, possibly due to the fear of high sovereign debt built up in most European economies leading to the European sovereign debt crisis that peaked in 2010 and 2012. Overall, we observe a rather heterogeneous pattern in the time variation of equity and debt flows across the sample of EMEs examined.

Table 1a displays the results of unit root tests for portfolio flows and stock market returns at both the time series-level and the panel data-level. For brevity, we report only the p-values of the test statistics. All tests are applied using two specifications, one with an individual intercept and one with an individual intercept and a time trend. To account for the dynamic structure of the data, these specifications are augmented to accommodate an autoregressive representation of order four. Next, each model is re-estimated successively by reducing one autoregressive term at a time using the Akaike Information Criterion in order to select the most suitable model for the data. The unit root tests are performed based on the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests, as originally proposed by Fuller (1976), Dickey and Fuller (1979, 1981), and Phillips and Perron (1988).

The tests suggest that equity and debt flows are stationary in levels as the null hypothesis of unit root is rejected at 5% and 10% statistical significance. Additionally, panel data unit root tests, specifically the LLC test proposed by Levin et al. (2002), and the IPS test of Im et al. (2003), are applied to the data. The former test assumes homogeneity in the unit root process for all cross-sectional units and estimates a pooled regression of an ADF-type specification for all markets simultaneously. The latter test allows for heterogeneity in the unit root process and estimates an individual ADF regression for each market separately. The panel unit root tests reported in Table 1a confirm our earlier finding that the series are stationary.

Table 1b presents the summary statistics of portfolio flows and stock market returns. The average equity flow values range from -0.012 (Czech Republic) to 0.083 (Chile), while average bond flows range from 0.023 (India) to 0.218 (Czech Republic). South Africa and Korea experience the greatest dispersion in equity flows, while Czech Republic and Bulgaria experience the largest fluctuations in bond flows. Portfolio flows present non-zero skewness values and excess kurtosis for the majority of the countries. The average stock market returns range from a low of -0.063 for Bulgaria to a high of 1.148 for Indonesia. These emerging economies experience high volatility in their stock market returns with seven out of nine markets in the sample exhibiting standard deviations over 5%. The presence of negative skewness and excess kurtosis further indicates that the stock market returns are non-normal.

2.2. Methodology

The parametric panel data framework used in the empirical analyses follows Cermeño and Grier (2006) and involves estimating an autoregressive model with a variance-covariance matrix that evolves as a generalized autoregressive conditional heteroskedastic (GARCH) process. As mentioned earlier, the panel GARCH methodology provides several advantages when compared with the conventional, OLS-based time-series or cross-sectional models by addressing not only possible conditional heteroskedasticity effects, but also cross-sectional interdependencies and individual heterogeneity across cross-sectional markets. In this approach, the conditional variances and covariances of the panel data are allowed to be time-varying. Originally proposed by Cermeño and Grier (2006), the model is an extension of the multivariate time series–based GARCH models to the panel dimension. GARCH models, introduced by Engle (1982) and later generalized by Bollerslev (1986), have enjoyed widespread popularity in the literature due to the fact that these models can successfully account for time dependent heteroskedasticity, in particular, the time-variation in return volatility and volatility persistence in that large (small) variance changes tend to follow large (small) variance changes. Next, we provide a description of the methodology adopted in our panel tests.

Let $R_{i,t} = \left(R_{1,t}, R_{2,t}, \ldots, R_{N,t}\right)'$ be a vector of stock market returns for t=1,2,…,T, i =1,2,…,N, where T and N represent the number of monthly observations and countries, respectively. The conditional mean for the return on stock market i in month $t$is modeled as a function of net debt and equity flows, after controlling for general capital market movements, as follows

$$R_{i,t} = \beta_{i,0} + \beta_1 R_{i,t-1} + \gamma_1 R_{W,t} + \gamma_2 Debt_{i,t} + \gamma_3 Equity_{i,t} + u_{i,t} \quad \textbf{(1)}$$

where $\beta_{i,0}$ is the constant of the panel regression, $R_{W,t}$ is the MSCI world stock market index return, and $Debt_{i,t}$ ($Equity_{i,t}$) are the total debt (equity) flows for country i, respectively. As will be discussed later, we examine alternative specifications for Equation (1) by including (or excluding) world market return ($R_{w,t}$) in the equation in order to check the robustness of the findings after controlling for the general capital market movements. It is assumed that all the characteristic roots of the lag polynomial $\left(1 - \beta_1 L - \ldots, \beta_p L^p\right) = 0$ lay inside the unit circle. This condition ensures that the process described in Equation (1) is stable, thus leading to a stationary panel. Also note that Equation (1) is designed to allow for cross-sectional homogeneity by having a single constant in the model (pooled regression), or for inter-individual heterogeneity by including a different constant, $\beta_{i,0}$, for each economy (fixed effects) in the same regression.

Proceeding with the conditional variance-covariance specification, let $u_{i,t} = (u_{1,t}, u_{2,t}, ..., u_{N,t})'$ be the vector of innovations obtained from Equation (1), with $u_{i,t} / \psi_{t-1} \sim N(0, \Sigma_t)$, where ψ_{t-1} is the information set available at time *t*-1.The conditional variance-covariance matrix Σ_t is assumed to be time-dependent heteroskedastic. Denoting the variance elements of Σ_t by $\sigma_{i,t}^2$ and the covariance elements by $\sigma_{ij,t}$ ($i \neq j$), the conditional variance for $R_{i,t}$ is designed to follow a GARCH (1,1) process described as

$$\sigma_{i,t}^2 = k_i + \theta_1 \sigma_{i,t-1}^2 + \varphi_1 u_{i,t-1}^2 + \delta_1 R_{W,t} + \delta_2 Debt_{i,t} + \delta_3 Equity_{i,t}, \ i = 1, ..., N \qquad \textbf{(2)}$$

In this specification, the conditional covariance terms are assumed to have a time-varying structure as

$$\sigma_{ij,t} = \rho_{ij} \left(\sigma_{i,t}^2 \sigma_{j,t}^2 \right)^{1/2}, \ i \neq j \qquad \textbf{(3)}$$

where ρ_{ij} is the correlation between stock markets *i* and *j*. The coefficients δ_j, $j = 1,2,3$ measure the effect of aggregate stock market movements, debt and equity flows, respectively on the conditional variance of stock market returns for a given country. Similarly, k_i is the constant of the conditional variance equation, respectively, θ_1 and φ_1 are the coefficients of the GARCH and ARCH terms in equation (2), respectively. Given that the dynamic panel-GARCH framework described above postulates not only the signs of the coefficients of the portfolio flow variables, but also their magnitudes, our estimations allow to test for the presence of portfolio flow effects on both the conditional mean and variance of stock market returns simultaneously. Note that, as in the case of the conditional mean equation, we examine alternative specifications for Equation (2) by including (or excluding) world market return ($R_{w,t}$) in order to check the robustness of the findings after controlling for the general capital market movements.

Regarding the estimation of the models, the procedure begins with expressing Equation (1) in matrix form as

$$\mathbf{R}_t = \mathbf{\Gamma_0} + \mathbf{\Gamma R}_{t-p} + \mathbf{u}_t, \quad t = 1,...,T \tag{4}$$

where $\mathbf{R}_t, \mathbf{\Gamma_0}$ and $\mathbf{u}_t$ are (N×1)-dimensional vectors of stock market returns, the constant, and the disturbance term, respectively, $\mathbf{R}_{t-p} = \left[R_{i,t-1}, R_{W,t}, Debt_{i,t}, Equity_{i,t}\right]$and $\mathbf{\Gamma} = \left[\beta_{1,}, \gamma_1, \gamma_2, \gamma_3\right]'$ .The log-likelihood function of the panel-GARCH model is then formulated as

$$L_t = -\frac{1}{2} NT \ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \log|\Sigma_t| - \frac{1}{2}\sum_{t=1}^{T}\left(\mathbf{R}_t - \mathbf{\Gamma_0} - \mathbf{\Gamma R}_{t-p}\right)' \Sigma_t^{-1}\left(\mathbf{R}_t - \mathbf{\Gamma_0} - \mathbf{\Gamma R}_{t-p}\right) \tag{5}$$

where the parameters for Equations (1)-(3)are estimated by maximizing this log-likelihood function using numerical methods. Under regularity conditions, the maximum likelihood estimator is shown to be consistent, asymptotically efficient and asymptotically normally distributed with the true parameter vector as the mean and the inverse of the corresponding information matrix as the variance-covariance matrix. Consequently, the asymptotic covariance-variance matrix of the maximum likelihood estimator is approximated by the inverse of the Hessian of the log-likelihood function evaluated at the parameter estimates.

The model described above is estimated in two steps. In the first step, an autoregressive model of order one is estimated via the least squares method

$$R_{i,t} = \beta_{i,0} + \beta_1 R_{i,t-1} + u_{i,t}, i = 1,..,N, t = 1,...,T \quad \textbf{(6)}$$

Next, the residuals from Equation (6) are substituted in the main model for the stock returns $R_{i,t}$, thus transforming Equation (1) to

$$\tilde{R}_{i,t} = \gamma_{i,0} + \gamma_1 R_{W,t} + \gamma_2 Debt_{i,t} + \gamma_3 Equity_{i,t} + u_{i,t} \quad \textbf{(7)}$$

where $\tilde{R}_{i,t}$ denote the residuals obtained from Equation (6). As discussed later, this approach filters out parametrically any possible linear dependence effects in the conditional mean specification.

3. Empirical Results

3.1. Misspecification Tests

We begin our analysis by conducting a battery of misspecification tests in order to ensure the adequacy of the statistical model described in the previous section, thus, the reliability of the statistical inferences in subsequent tests. Table 1c reports the results of various misspecification tests applied to two alternative specifications for Equations (1) and (2) that include (or exclude) the world market return ($R_{w,t}$) in the model. Panels A and B in the table report the results of the misspecification tests for the conditional mean and variance-covariance, respectively. Individual effects test for the presence of individual homogeneity in the conditional mean and individual effects with HAC test for the presence of individual homogeneity using a Wald test based on HAC standard errors. Serial correlation refers to Wooldridge (2002) test for the presence of serial dependence in the residuals of the conditional mean and cross-sectional independence refers to Pesaran's (2004) CD test for the presence of cross-sectional independence. Finally, ARCH effects refer to an AR(3) model of squared residuals and cross products of lagged residuals (we report the t-test values in the table).

We begin the misspecifications tests by testing for the presence of individual effects in the conditional mean equation. For this purpose, we first estimate Equation (1) using the Least Squares Dummy Variables method (LSDV) and next test the null hypothesis that all cross-sectional dummy variable coefficients are jointly equal to zero by means of an F-test. We also report in the table the results of a Wald test for the null hypothesis of cross-sectional homogeneity based on robust standard errors, estimated using Arellano (1987) heteroskedasticity and autocorrelation consistent covariance (HAC) estimator.[6] The test results indicate strong support of the null hypothesis of no individual effects for both specifications, thus providing support for data poolability. Next, we test for serial correlation in the innovations of both models with the help of several diagnostics proposed by Wooldridge (2002) for linear autocorrelation in panel regression models. Following this approach, we first regress stock market returns against portfolio flow variables and lagged innovations. Next, we examine the statistical significance of the coefficient of each lagged innovation using a t-test with HAC standard errors. As reported in the table, the findings reject the null hypothesis of no serial correlation up to three lags, consistently for both specifications, pointing to the presence of serial correlation in the panel data, thus justifying the use of the filtering technique described in Equation (6).

Next, we proceed with the diagnostic tests that help us determine the most suitable conditional variance-covariance model parameterization of the data. We begin by investigating for the presence of significant cross-sectional independence for each pair of stock markets. In this procedure, observing $\sigma_{ij} = 0,\ i \neq j$ for a given pair of stock markets implies cross-sectional independence and thus, Equation (3) should be ignored, necessitating the use of a reduced form of

[6]Arellano (1987) estimator is an extension of White (1980) and Newey and West (1987) Heteroscedasticity and Autocorrelation Consistent (HAC) variance – covariance estimator to the panel level.

the log-likelihood function in order to estimate model parameters. Conversely, if cross-sectional dependence is present, then the log-likelihood function in Equation (5) holds. For this purpose, we used the CD test by Pesaran (2004) and test the null hypothesis $H_0 : \sigma_{ij} = 0$ applied to the residuals of Equation (1). As shown in the table, the test statistic values strongly reject the null hypothesis of cross-sectional independence of the residuals, consistently for either specifications that include (or exclude) world market return in the equation. Hence, we conclude that Equation (5) constitutes a suitable log-likelihood function.

We also implement a diagnostic test about ARCH effects in the data following the approach introduced by Cermeño and Grier (2006). In this approach, first, the residuals from an autoregressive model of order three [AR (3)] of the stock market returns are estimated. Next, the squared values of the residuals are regressed against the lagged squared residuals and all two-way interactions between lagged residuals. A standard t-test is used to examine the statistical significance of each lagged squared residual and cross-product coefficient in order to test for time-dependence in the conditional variance and covariance, respectively. Panel B in Table 1c presents the t-test values and the corresponding p-values. We observe that ARCH effects exist up to 3 lags for the first specification that includes world market return and that there is a significant cross-product coefficient. In the case of the second specification that does not include the world market return, we see that ARCH effects are present at two lag points with all cross-product coefficients highly significant. Thus, our evidence suggests that the variance and covariances of the panel stock market returns exhibit significant time-variation.

Finally, we examine individual effects in the conditional variance equation via the null hypothesis of individual homogeneity in the variance $H_0 : k_i = k$ (see Equation 2) by testing that all cross-sectional dummy variable coefficients are jointly equal to zero using an F-test. The null hypothesis of individual homogeneity in the variance is rejected for the first specification only, suggesting that separate constant terms should be included in the conditional variance equation in order to model individual heterogeneity.

In sum, the misspecifications test results suggest that an autoregressive structure is required for the conditional mean specification with a single constant for all cross-sectional units due to poolability. For comparison purposes, however, we present in subsequent tables the estimates using both cross-sectional fixed effects and pooled regression. At the same time, our findings also indicate the presence of time dependence and individual heterogeneity in the variance dynamics of the panel stock market returns. Moreover, not surprisingly, we observe significant cross-dependencies among the stock markets, while the pattern of cross-dependencies is time-varying. As a result, we parameterize conditional variance-covariance dynamics by means of a GARCH model, while individual constants for the cross-sectional units are utilized in the variance-covariance equations due to heterogeneity in the variance and the presence of cross-sectional dependence.

3.2. Baseline Model Results

Table 2 presents the estimation results for the conditional mean and variance-covariance equations described in Equations (1)-(3). Panels A and B in the table present the findings for the conditional mean and variance equations, respectively.[7] The conditional mean equation for models A and B is described in Equation (1) where $R_{w,t}$ is the MSCI world stock market index return for month t and $Debt_{i,t}$ ($Equity_{i,t}$) are the country-specific debt (equity) flows. The conditional variance and covariance of each model is given in Equations (2)-(3). Models C and D have the same setup

[7] To save space, we do not report the estimates of the conditional covariance specification in Equation (3); these results are available upon request.

as Models A and B except that the world market return ($R_{w,t}$) is excluded from both the conditional mean and variance equations. Models A and C are estimated as a panel regression with cross-sectional fixed effects, while models B and D are estimated as a pooled regression. Both regressions have GARCH type errors, given by Equations (2) and (3), thus the coefficients are estimated using the maximum likelihood method described earlier. Finally, $Equity_t$ and $Debt_t$ are multiplied by 100 to enhance the optimization process for maximum likelihood estimation.

Examining the findings in Panel A, in line with standard asset pricing models, we see that the coefficient for the world stock market return is highly significant and positive, highlighting positive risk exposure of individual stock markets to aggregate capital market movements. The coefficient for debt flows, however, is found to be highly significant and negative in all parameterizations of the conditional mean and variance equations, even after controlling for aggregate market effects. We observe that net debt flows are generally associated with a negative marginal wealth effect on emerging stock markets, while equity flows generally have an insignificant effect on stock market returns. In an earlier study, focusing on Latin American and Asian countries, Chuhan et al. (1998) show that equity flows are more sensitive to global factors than bond flows. Given this, one can argue that aggregate capital market effects absorb the explanatory power of equity flows in our tests. Nevertheless, the initial findings suggest that debt flows contain significant explanatory value over stock market returns that is not captured by aggregate market movements or equity flows.

Moving on to Panel B, we see that the coefficients for the ARCH and GARCH terms are highly significant with their sum close to unity, in line with empirical evidence of volatility persistence in financial market returns (e.g. Ding et al., 1993). We also observe a negative and highly significant effect of world market return on volatility, in line with the well-documented "leverage effect" which refers to the empirical evidence of a negative relationship between asset returns and volatility (e.g. Christie, 1982). Examining the results across the stock markets, we observe highly significant constant terms, with Brazil (South Africa) experiencing the highest (lowest) return volatility. More importantly and consistent with the findings in Panel A, we see that stock market volatility is highly sensitive to debt flows, consistently across all four specifications, such that an increase (decrease) in net debt flows is associated with lower (higher) stock market return volatility, while equity flows once again have generally insignificant effects.

Recently, Balcilar et al. (2020) show that credit rating announcements for BRICS and PIIGS economies are generally stronger and more widespread in the case of stock market volatility than returns, while the credit rating effect on volatility is driven mostly by rating upgrades rather than downgrades. Considering the finding by Chuhan et al. (1998) that bond flows, compared to equity flows, are more sensitive to a country's credit rating than global factors, our findings suggest that the negative volatility effect of bond flows reflects market sentiment around positive credit ratings announcements, which cannot be captured by equity flows. To that end, the findings suggest that bond flows possess informational value over and above that is captured by equity flows as well as aggregate market movements.

In a recent study, Pandolfi and Williams (2019) note that capital inflows improve liquidity in sovereign debt markets, implying that the finding of a negative debt flow effect on volatility may be explained by improved liquidity conditions as a result of debt flows. In order to formally examine the role of market liquidity, we control for liquidity in each stock market using the liquidity measure of Vagias and van Dijk (2011) and Karolyi et al. (2012) that is based on the illiquidity measure of Amihud (2002). Specifically, we calculate, for each stock market, the monthly liquidity measure, LIQ_t, as $-\log(1+ILLIQ_t)$ where $ILLIQ_t$ is the monthly average of the ratio of daily absolute stock market index returns to its dollar volume, as proposed in Amihud (2002). The dollar volume is determined as the product of stock price index value and the corresponding trading volume.

Table A1 in the Appendix presents the estimation results for the effect of fund flows on stock market return and risk after controlling for market liquidity. Note that the monthly ratios are multiplied by 1000000 to ease the optimization procedure. Consistent with the literature, we observe that liquidity generally has a negative effect on stock market volatility, while its effect on conditional means is largely insignificant. At the same time, we also observe that our findings in Table 2 still hold, implying a significant effect of debt flows on both stock return and volatility. Thus, we confirm that the effect of debt flows on stock market volatility cannot be explained by improved liquidity conditions. Overall, the findings from the baseline model suggest that debt flows possess incremental information regarding stock market return dynamics that is not captured by equity flows nor broad capital market movements. This is indeed valuable information for both investors as well as market regulators as signals contained in debt flow data can be utilized to improve models of risk and return in emerging stock markets.

In order to provide further insight to the inferences from the baseline model, we present in Table 3 the findings for two subsamples (2/2005 to 12/2008) and (1/2009 to 3/2017) using the global financial crisis as the cutoff point. Several interesting observations emerge from the comparison of the two sub-periods. First, we see that the significant effect of debt flows on emerging stock markets, reported in Table 2, are largely driven by the second sub-period, which corresponds to the post-global financial crisis period. Taylor and Sarno (1997) argue that U.S. interest rates constitute the most important determinant of the short-run dynamics of bond flows, in particular, to developing countries. Given the significant structural changes in the conduct of monetary and fiscal policies as a response to the 2007/2008 financial crisis and prolonged periods of ultra-low interest rates in advanced economies, it is not unexpected to see stronger effects of debt flows on EME stock markets during the post-crisis period. James et al. (2014) note that portfolio, especially debt, flows to major advanced economies have declined sharply following the global crisis, while debt flows to emerging economies have been strong, fueled by the resilience in emerging market corporate bond issuance. Therefore, the relatively stronger debt flow effect, particularly during the post-crisis period, could be due to bond flow patterns in favor of EMEs during this period.

Interestingly, we also see in Table 3 that equity flows gain significant explanatory power over both stock market returns and volatility during the second subsample, with equity flows commanding a positive marginal effect on stock market returns. Eichengreen (2010) notes that emerging economies fared substantially better than advanced economies during the global crisis. Therefore, the increasing role of equity flows as a driver of return dynamics in emerging stock markets during the post-crisis period may reflect global investors' favourable expectations over EMEs or short-term positive effects due to hot money flows, propping up stock prices. Interestingly, although world market return is highly significant during both sub-periods, we observe lower coefficient estimates for R_{wt} during the post-crisis period, suggesting that equity flows absorb some of the explanatory power of the world market return over emerging stock markets during the post-crisis era. These findings are in line with the evidence in Shin (2013) that portfolio bond and equity flows have played a pivotal role in capital flows to emerging market economies during and after the financial crisis.

Finally, equity flows (along with debt flows) are found to affect stock market volatility particularly during the second sub-period, indicating a negative fund flow effect on return volatility regardless of the source of the flow (equity or debt), perhaps as fund flows reflect information arrival to the market, which in turn, helps dissipate market uncertainty. In sum, the findings from the baseline model suggest that fund flows (both equity and debt) contain significant explanatory value over both stock market returns and volatility that is not captured by broad market movements, while equity flows assume significant explanatory power, particularly during the post-global financial crisis period. These results imply that emerging stock markets have become particularly sensitive to fund flows during the post-crisis period, with significant wealth and risk effects.

3.3. Controlling for Leverage and Asymmetric Effects

A well-established strand of the literature documents the presence of a so-called "leverage effect" in financial returns, postulating a negative relationship between asset returns and volatility, in which rising asset prices are accompanied by a decline in volatility (and vice versa).[8] Furthermore, a number of studies including Ang, et al (2006), Lundblad (2007) and Adrian and Rosenberg (2008) document a link between excess stock returns and market volatility in an asset pricing framework. Considering the evidence that establishes a link between global volatility and cross-border capital flows (e.g. Forbes and Warnock, 2012; Rey, 2018), it is possible that our finding of a negative debt flow effect on stock market returns is in fact driven by aggregate stock market volatility through leverage effects and not necessarily debt flows. Therefore, in order to examine the robustness of our inferences to the possible presence of a leverage effect, we extend the baseline model by including a proxy of world stock market volatility in both the mean and variance specifications as

[8]See Bekaert and Wu (2000) for a discussion of the different interpretations of the leverage effect.

$$R_{i,t} = \beta_{i,0} + \beta_{i,1} R_{i,t-1} + \gamma_1 R_{Wt} + \gamma_2 Debt_{i,t} + \gamma_3 Equity_{i,t} + \gamma_4 VR_{Wt} + u_{i,t} \quad \textbf{(8a)}$$

$$\sigma_{i,t}^2 = k_i + \theta_1 \sigma_{i,t-1}^2 + \phi_1 u_{i,t-1}^2 + \delta_1 R_{Wt} + \delta_2 Debt_{i,t} + \delta_3 Equity_{i,t} + \delta_4 VR_{Wt}, \; i = 1, \ldots, N \quad \textbf{(8b)}$$

where VR_{Wt} is a proxy for the world stock market volatility, obtained as the conditional volatility estimates from a GARCH(1,1) model fitted to world stock market returns (R_{Wt}).[9] This extended model allows us to analyze the impact of portfolio flows on the conditional moments of emerging market returns when considered jointly with a factor that is a proxy for aggregate world market volatility. Once again, we examine alternative variations with and without the world market return in the conditional moment equations.

Table 4 presents the estimation results for the conditional mean and variance-covariance equations described in Equations (3), (8a) and (8b). Panels A and B present the findings for the conditional mean and variance equations, respectively. Models C and D have the same setup as Models A and B except that the world market return is excluded from the equations. Models A and C are estimated as a panel regression with cross-sectional fixed effects, while models B and D are estimated as a pooled regression. While the negative effect of debt flows remains robust to the inclusion of world market volatility, we observe that equity flows loses significance in most model specifications. Furthermore, we observe a positive association between the aggregate and country-level stock market volatilities, implied by positive estimates for γ_4, suggesting that an increase in aggregate market volatility positively affects volatility at the country level, highlighting the role of global economic integration and market interdependencies. Overall, the additional tests provide further support to the effect of debt flows on emerging stock return dynamics, while limited evidence on the impact of equity flows is observed.

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[9] Although not reported due to space considerations, the use of VIX as an alternative proxy for global risk yields similar results (available upon request).

Motivated by the evidence of an asymmetric leverage effect in which negative price shocks have a greater impact on volatility than positive shocks (e.g. Engle and Ng, 1993), we further extend our baseline model to incorporate possible asymmetries in the volatility process. The most popular GARCH-type models incorporating asymmetric effects include the exponential GARCH (EGARCH) (Nelson, 1991) and the GARCH-GJR (Glosten et al., 1993) specifications. In our application, we generalize the GARCH-GJR model to the panel level by including an asymmetric effect term, similar to that in Glosten et al. (1993), in the conditional variance specification of Equation (2) as follows

$$\sigma_{i,t}^2 = k_i + \theta_1 \sigma_{i,t-1}^2 + \phi_1 u_{i,t-1}^2 + \phi_2 I\left\{u_{i,t-1} < 0\right\} u_{i,t-1}^2 + \delta_1 R_{W,t} + \delta_2 Debt_{i,t} + \delta_3 Equity_{i,t},\ i = 1,...,N, t = 1,..,T \quad \textbf{(8c)}$$

where $I\{u_{i,t-1} < 0\}$ is an indicator function that takes on the value 1 if $u_{i,t-1} < 0$ and 0 otherwise. In this specification, negative shocks $(u_{i,t-1} < 0)$ and positive shocks $(u_{i,t-1} > 0)$ are allowed to have a heterogeneous effect on the volatility process, implied by a significant and positive estimate for φ_2. If, however, $\varphi_2 = 0$, Equation (8c) reduces to the symmetric panel GARCH model. As in the case of the symmetric panel GARCH model, we assume normally distributed errors, allowing the use of the log-likelihood function shown in Equation (5).

Table 5 presents the estimation results for the asymmetric panel GARCH model described in Equation (8c). Models C and D have the same setup as Models A and B except that the world market return ($R_{w,t}$) is excluded from the conditional moment equations. The findings indicate the presence of asymmetric leverage effects in the volatility process, implied by positive and significant estimates for φ_2.We also observe in models C and D that the coefficient φ_2 is larger than φ_1 (i.e., ARCH parameter coefficient), indicating that negative shocks have a more profound effect on stock return volatility than positive shocks. Having established the presence of asymmetric effects of return shocks on volatility, we see that the effect of debt flows on volatility is robust, while the effect on the conditional mean partially holds. Similarly, equity flows are found to have mostly insignificant effects on volatility, consistent with the baseline model results for the whole sample. Accordingly, the additional tests provide support for the robustness of a significant debt flow effect on emerging market return dynamics, even after controlling for world market return, volatility as well as leverage and asymmetric effects.[10]

3.4. Portfolio Flows and Idiosyncratic Risk

In the last part of our analysis, we supplement our findings by exploring whether portfolio flows have any effect on idiosyncratic risk in emerging stock markets. Clearly, from a traditional portfolio diversification perspective, one would expect idiosyncratic volatility to be completely diversified away as investors hold well-diversified portfolios, allowing to eliminate diversifiable (or asset-specific) risks. This may very well be the case for a market in which capital flows freely and investors have access to a large number of investable assets without significant market frictions or transaction costs. However, as in the case of many emerging economies, this basic assumption may not necessarily hold as investors often find limited diversification tools and hedging instruments available in their local markets, leaving them exposed to risk factors that would normally be considered diversifiable. Indeed, a number of studies including Malkiel and Xu (2000) and Goetzmann and Kumar (2004), among others, show that investors are unable to hold well diversified portfolios, and therefore demand compensation for their inability to diversify risk. This, in turn, leads to a risk premium embedded in asset returns driven by idiosyncratic volatility, possibly more significantly in emerging stock markets.

[10] Motivated by Yan et al. (2016), we also estimated the model by controlling for bank credit flows, measured by total credit from all sectors to the private non-financial sector, and found similar results (available upon request).

In order to examine whether fund flows have any significant effects on idiosyncratic risk in emerging markets, we follow the approach by Malkiel and Xu (2000) and compute idiosyncratic volatility (IV) as the variance of the residuals from the model of stock market returns against the global market, size and book-to-market factors by Fama and French (1993). More specifically, we estimate for each stock market

$$R_{it} - R_{ft} = \beta_{i0} + \beta_{i1}\left(R_{Mt} - R_{ft}\right) + \beta_{i2} SMB_t + \beta_{i3} HML_t + \varepsilon_{it} \tag{9}$$

where R_{it} is the stock market index return for a given country i, R_{Mt} (R_{ft}) are the world stock market return (risk-free rate) and SMB_t (HML_t) are the global size (book-to-market) factors. We then use the residuals (ε_{it}) to construct two alternative idiosyncratic volatility series at the country level as $IV_{it} = \varepsilon_{it}^2$ and $IV_{it} = \left|\varepsilon_{it}\right|$.[11] Next, idiosyncratic volatilities are stored in panel form, i.e., $IV_{i,t}$, in which they are used as the dependent variable in the following panel model

$$IV_{i,t} = \gamma_{i,0} + \gamma_1 R_{W,t} + \gamma_2 Debt_{i,t} + \gamma_3 Equity_{i,t} + u_{i,t} \tag{10}$$

$$u_{i,t} / \psi_{t-1} \sim N\left(0, \Sigma_t\right) \tag{11}$$

$$\sigma_{i,t}^2 = k_i + \theta_1 \sigma_{i,t-1}^2 + \varphi_1 u_{i,t-1}^2 + \delta_1 R_{W,t} + \delta_2 Debt_{i,t} + \delta_3 Equity_{i,t},\ i = 1,\ldots,N \tag{12}$$

$$\sigma_{ij,t} = \rho_{ij}\left(\sigma_{i,t}^2 \sigma_{j,t}^2\right)^{1/2},\ i \neq j \tag{13}$$

Table 6 presents the estimation results for the conditional mean and variance-covariance equations described in Equations (10)-(13).[12] Panels A and B present the findings for the conditional mean and variance, respectively. Models B and D have the same setup as Models A and C except that the world market return ($R_{w,t}$) is excluded from the equations. Our findings

[11]Several method shave been proposed to measure idiosyncratic volatility (IV). For example, Drew et al. (2004) measure IV as the difference between total risk and the systematic risk, while Ang et al. (2009) and Fu (2009) use the standard deviation of the residuals obtained from Fama- French regression.

[12] Squared residuals are divided by 10 in order to enhance the optimization procedure.

generally suggest a negative association between idiosyncratic volatility and portfolio flows, with debt flows generally commanding a more consistent effect on IV compared to equity flows. We note that model A fits the data better, implied by a larger log-likelihood value and that the explanatory power of flow variables over IV is absorbed by the world market return when it is introduced to the model (comparing Models A and B). However, portfolio flows are found to be significant when considered alone, particularly in the case of IV defined in terms of squared residuals. Overall, the results suggest that debt flows have a significant negative effect on idiosyncratic risk while the effect of equity flows is rather limited to how IV is computed. From an economic perspective, the findings suggest that net capital inflows to emerging stock markets can help lower country-specific risks, which could be an important consideration when it comes to the risk premia associated with these markets and the cost of capital estimations for capital budgeting decisions.

Similar results are found in the case of conditional variance of stock market returns reported in Panel B. While the negative effect of debt flows the conditional variance of IV is robust, equity flows are also found to have limited negative effects as well. Such a relationship between the volatility-of-volatility and portfolio flows has significant investment implications as it implies that even a small change in portfolio flows could induce a critical effect on the tail behaviour of the return distributions. Our findings suggest that a change in both debt and equity flows yield a negative effect on the conditional fourth-moment measures of the returns, indicating that portfolio flows, particularly net debt inflows, decrease the likelihood of crash risk. Clearly, the finding that debt flows are a significant determinant of crash risks in emerging stock markets has significant implications for future analysis given the econometric studies that highlight the importance of co-dependencies between different quantiles of the conditional distribution of financial returns and not just co-movements focusing on the first two moments.[13]

3.5. Test of reverse-causality

Since our results from the baseline model do not take into consideration the possible effect of reverse causality, viz. the effect from stock returns to capital flows, we perform additional tests to check the robustness of our findings from the baseline model.[14] Our model assumes that portfolio flows are exogenous variables, which implies that they are determined outside the system described by our model. This assumption is in line with the evidence of a global financial cycle in capital flows that co-moves with the volatility index, VIX, and risk aversion in global markets (Rey, 2018) and that a global factor, driven by the time-varying market-wide risk aversion as well as U.S. monetary policy, explains a significant part of the variation in the cross-section of global asset returns (Miranda-Agrippino and Rey, 2015). In the case of emerging market economies, the assumption of exogeneity for portfolio flows is consistent with the role of U.S. monetary policy as a driver of credit growth in the U.S. as well as cross-border credit flows in emerging economies (e.g. Anaya et al., 2017).

If the assumption of exogeneity holds, then the maximum likelihood estimator can be used to obtain unbiased, consistent and effective estimates of the model parameters. If, on the other hand, portfolio flows are endogenous variables, i.e. they are jointly determined with stock market returns, then the use of the maximum likelihood estimator may prove to be problematic. From an econometric standpoint, the maximum likelihood estimators of the model parameters may be inconsistent under the presence of endogenous explanatory variables. For this reason, following

[13]For instance, see the research of Embrechts et al. (2000), Straetman et al (2008), Hartmann et al., (2004), Longin and Solnik (2001), Poon et al. (2004), among others.

[14] We thank an anonymous reviewer for the suggestion to check for reverse causality in our tests.

the econometric literature, we applied the instrumental variables (IV) approach to our original setting in order to deal with the possible presence of endogeneity bias, which in turn may result in inconsistent coefficient estimates and misleading inferences. Under this approach, we first estimated auxiliary panel regressions using debt and equity flows as dependent variables. A list of fixed, small dimension instrumental variables is employed in these specifications. Then, the portfolio flow variables in equations (1)-(3) are substituted by the fitted portfolio flows obtained from these auxiliary regressions.

The auxiliary specifications which are used to generate the new portfolio flows are as follows

$$Debt_{i,t} = \alpha_{i,0} + \sum_{j=0}^{5} \beta_j dDebt_{i,t-j} + u_{i,t} \qquad \text{(A1)}$$

$$Equity_{i,t} = \alpha_{i,0} + \sum_{j=0}^{5} \beta_j dEquity_{i,t-j} + u_{i,t} \qquad \text{(A2)}$$

where $dDebt_{i,t}$, and $dEquity_{i,t}$ represent the first difference of debt and equity flows, respectively. Equations (A1) and (A2) are estimated by OLS allowing for cross-sectional fixed effects. The fitted values of the dependent variables are then used to represent the instrumented portfolio flows. Although the empirical practice recommends the use of the lagged values of the independent variables as instrumental variables, we preferred the first difference as well as lagged differences, because the former are found to perform poorly. A small number of lags of the differenced variables ensures any efficiency loss will be avoided.

The standard approach in IV estimation examines whether the assumption of instrument relevance holds, i.e. the instrumental variables are partially and sufficiently related to portfolio flows controlling for other explanatory variables. Table A2 in the Appendix reports the results for the F-statistics of the joint significance of the instruments as well as the F-statistics for the individual significance of each instrument. Panels A and B in the table present the findings for the auxiliary regressions for debt and equity flows on their instruments, respectively. Note that we also test the relevance of the instruments in terms of a second auxiliary regression where we control for world stock market effects. Evidence of weak instruments is implied by small values of the F-statistics (a rule-of-thumb states smaller than 10). We observe in the table that all F-statistics take on very large values in both equity and debt flow specifications reported in Panels A and B, respectively. Hence, we find no evidence of weak instruments, suggesting that we can use the specific instruments to generate fitted portfolio flow values, which in turn will be used as substitutes of the original variables in our model to remove possible endogeneity bias.

Table A3 in the Appendix reports the estimation results for the conditional mean and variance-covariance equations described in Equations (1)-(3) based on the instrumented portfolio flows. All models are estimated as a panel regression with cross-sectional fixed effects. Models (A) and (B) present the estimation results of our baseline model. In addition to the baseline model, following the other comments on the robustness of our findings, we also report in Models (C) to (F) the estimation results when we control for bank credit flows ($Credit_{i,t}$) and world stock market volatility ($VR_{W,t}$). The results are consistent with our previous findings. The coefficients of debt flows are highly significant in four out of six models and negative in the conditional mean of the stock market returns. On the other hand, we find limited evidence that equity flows affect positively the mean equation for stock market returns. We observe that debt flows have a highly significant and negative effect on the conditional variance of the returns, while equity flows do not influence the stock return volatility. Overall, these additional tests indicate that our findings from the baseline model are indeed robust.

4. Conclusion

The rise in the financial integration of global capital markets has resulted in a dramatic increase in international capital flows, which in some cases, has led to disastrous outcomes as significant capital inflows driven by risk appetite were followed by sudden outflows, devastating local economies and crashing currency values. This is an issue of high concern not only for investors but also policy-makers, particularly in emerging markets that tend to be more vulnerable to external cash flow shocks due to the nature of their risk exposures with respect to global factors. Accordingly, it is imperative to understand the possible impact on the economy due to flows of capital for the obvious policy-making reasons.

Despite the multitude of studies on the effect of cross-border capital flows on financial market returns, very few studies, however, have focused on the composition of flows, viz. equity and debt flows, and its relative effect on equity returns. Earlier studies including Taylor and Sarno (1997) and Chuhan et al. (1998) note that equity and bond flows exhibit heterogeneous patterns in terms of their sensitivity to global and domestic factors, while Krugman (2000) highlights the importance of debt flows as they are more likely to exacerbate cycles in asset prices and can encourage risky lending during economic booms. Our work extends the strand of literature that evaluates the significance of capital flows in driving emerging market returns from a novel perspective by distinguishing between equity and debt flows for nine emerging market economies (EMEs) and examining the effect of capital flows on stock market return, volatility as well as idiosyncratic risks via the parametric panel data framework proposed by Cermeño and Grier (2006).

We show that fund flows (both equity and debt) possess incremental information over emerging stock market returns and volatility, particularly during the post-global financial crisis period. Relative to equity flows, we observe that debt flows generally have a stronger and more consistent effect on both stock market returns and volatility. The effect of debt flows is robust even after controlling for bank credit flows, aggregate capital market movements, global risk, and country-level liquidity factors. Interestingly, we find that equity flows assume significant explanatory power particularly during the post-global financial crisis period, even absorbing some of the explanatory power of aggregate market movements during this period. The findings overall suggest that emerging stock markets have become particularly sensitive to fund flows during the post-crisis period, with significant wealth and risk effects.

Further analysis shows that changes in debt flows can serve as a significant determinant of crash risks in emerging stock markets, which is an important consideration given the evidence of co-dependencies at extreme quantiles of the conditional distribution of financial returns across global markets. Finally, our findings also indicate a significant effect of debt flows on idiosyncratic risks at the country level, while the effect of equity flows is rather limited to the measure of idiosyncratic volatility used in the analysis. From an economic perspective, the findings suggest that net capital flows to emerging stock markets, particularly debt flows, have significant wealth and risk effects, while they can help lower country-specific risks. This is an important consideration when it comes to the risk premia associated with emerging market valuations and the cost of capital estimations for capital budgeting decisions. Further research could build on these results and explore whether the informational content of debt flows can be utilized to improve models of risk and return in emerging stock markets with further extension to portfolio diversification applications.

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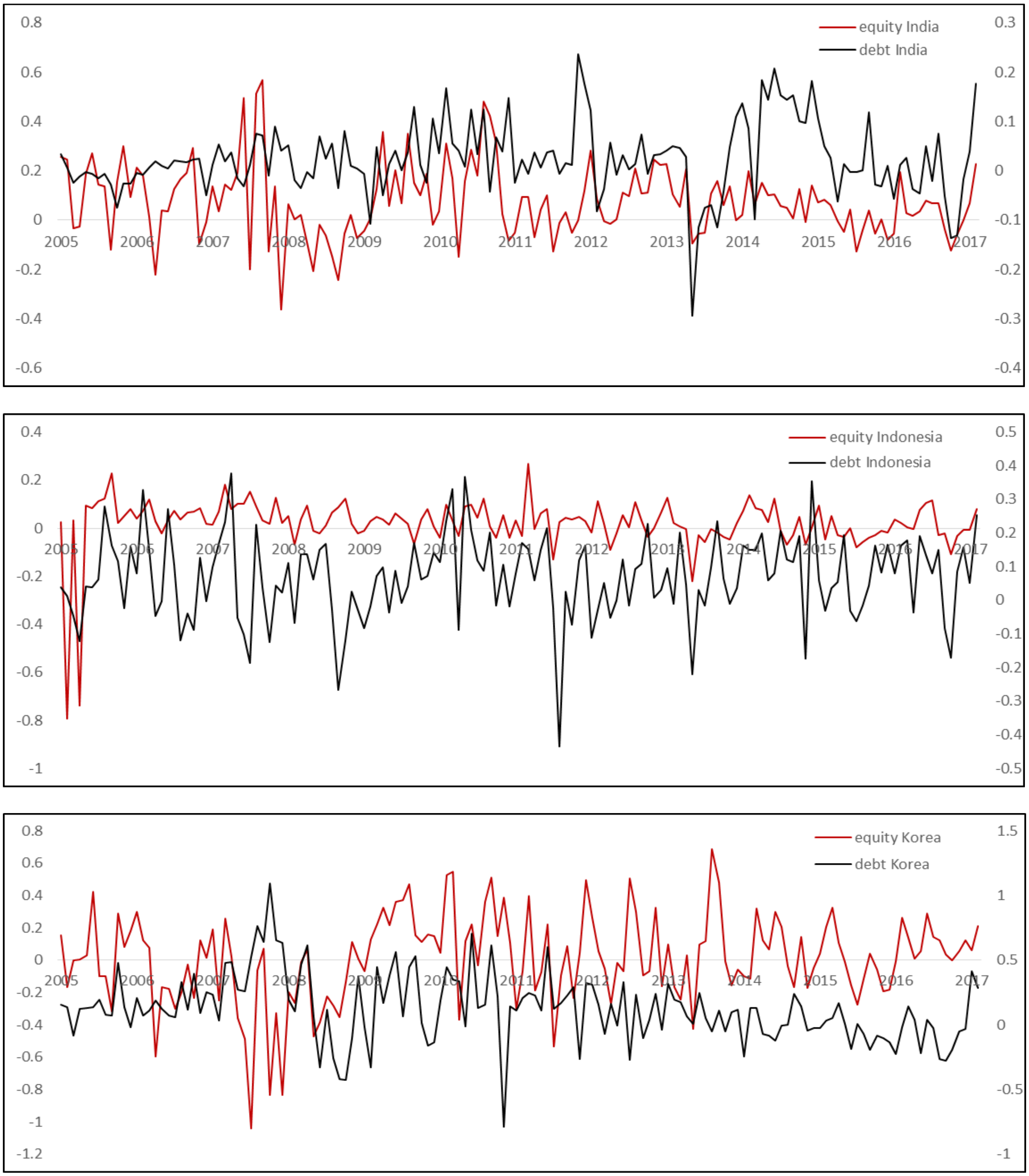
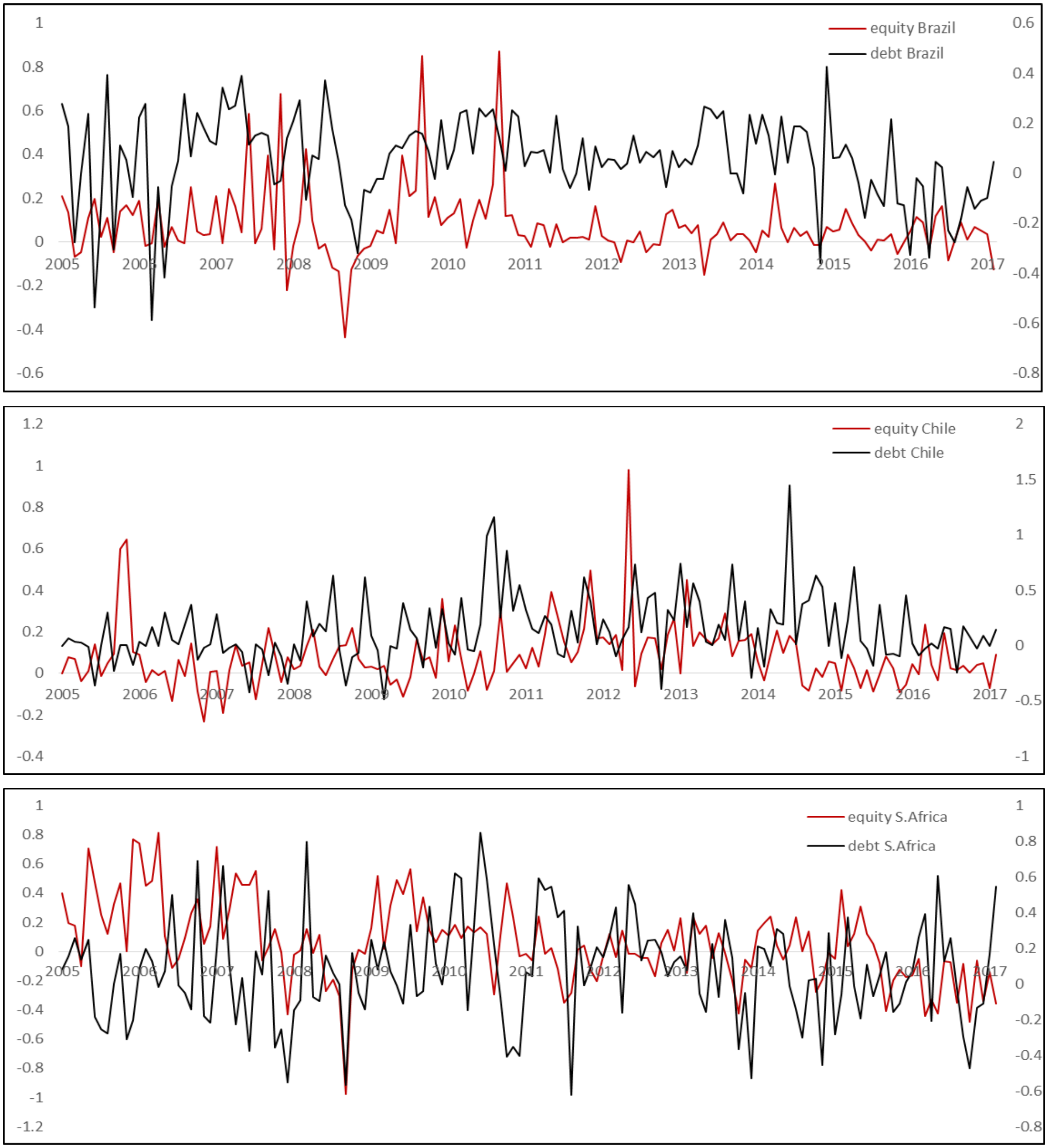
Figure 1: Equity and Debt flows of India, Indonesia and South Korea



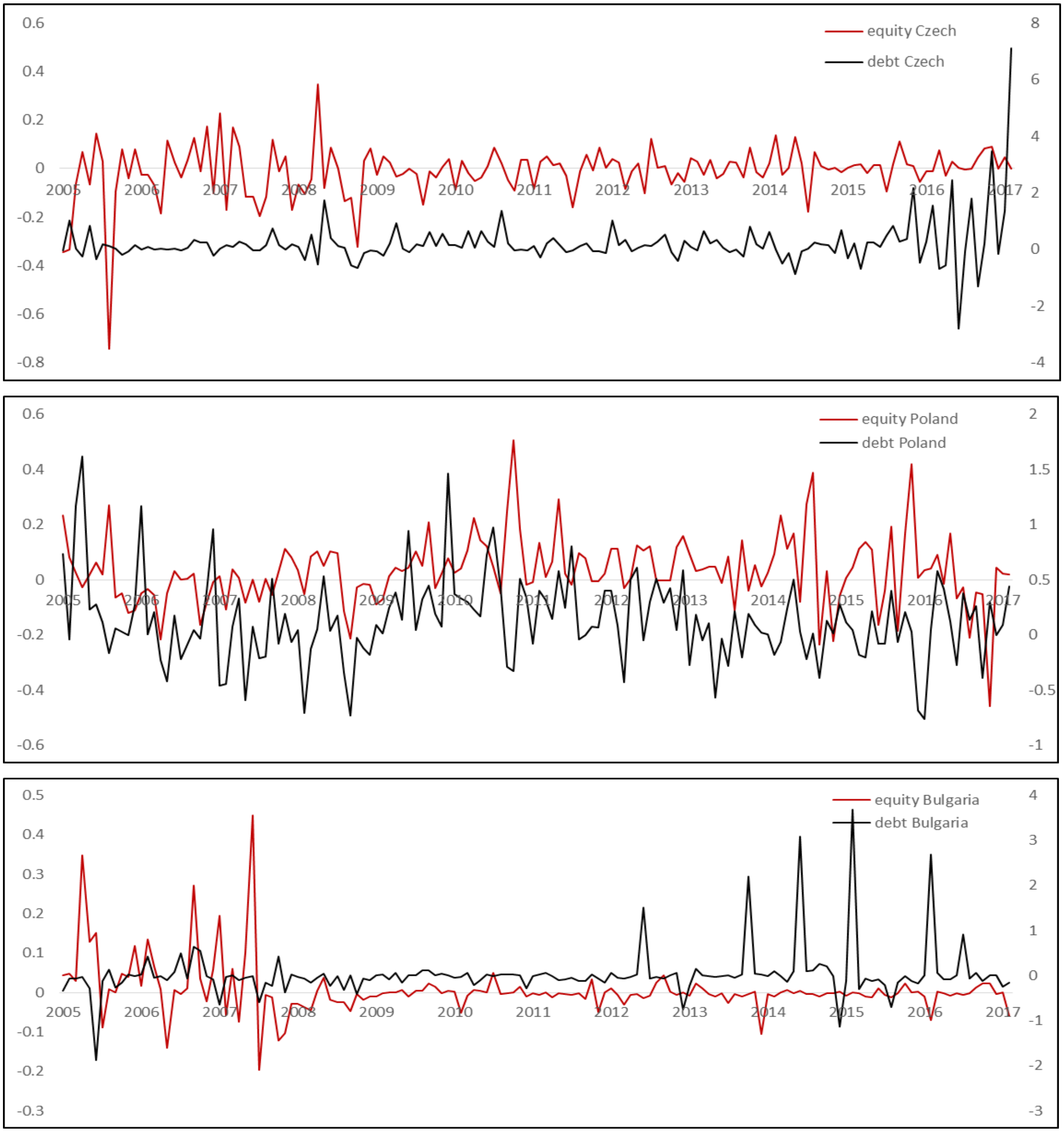
Note: The figure presents the monthly equity and debt flow for India, Indonesia and South Korea over the period from January 2005 to March 2017. The flows for these countries are measured by net non-resident purchases of equities or bonds as a percentage of the GDP.

Figure 2: Equity and Debt flows of Brazil, Chile and South Africa



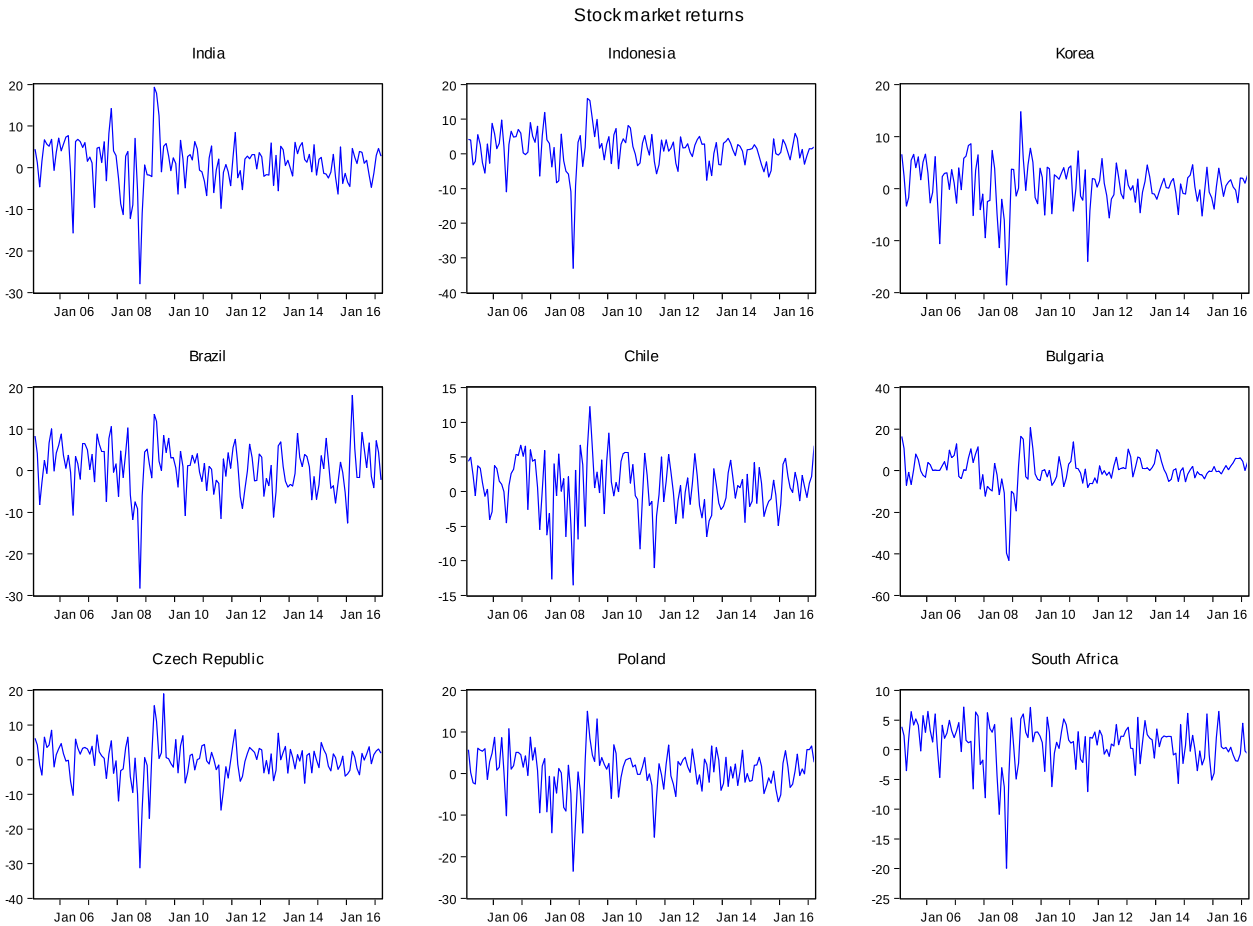
Note: The figure presents the monthly equity and debt flow for Brazil, Chile and South Africa over the period from January 2005 to March 2017. The flows for these countries are measured by net non-resident purchases of equities or bonds as a percentage of the GDP.

Figure 3: Equity and Debt flows of the Czech Republic, Poland and Bulgaria



Note: The figure presents the monthly equity and debt flow for the Czech Republic, Poland and Bulgaria over the period from January 2005 to March 2017. The flows for these countries are measured by net non-resident purchases of equities or bonds as a percentage of the GDP.

Figure 4: Stock Market Returns



Note: The figure presents the monthly stock market returns for Brazil, Bulgaria, Chile, Czech Republic, India, Indonesia, Korea, Poland and South Africa over the period January 2005 to March 2017.

Table 1a: Unit Root Tests

	Time series unit root tests				Panel data unit root tests			
	intercept		intercept and trend		intercept		intercept and trend	
	ADF	PP	ADF	PP	LLC	IPS	LLC	IPS
	Panel A: *Equity flows*							
India	0.002	0.000	0.009	0.000	0.000	0.000	0.000	0.000
Indonesia	0.000	0.000	0.000	0.000				
Korea	0.004	0.000	0.010	0.000				
Brazil	0.004	0.000	0.009	0.000				
Chile	0.002	0.000	0.012	0.000				
Bulgaria	0.000	0.000	0.000	0.000				
Czech R.	0.000	0.000	0.000	0.000				
Poland	0.002	0.000	0.008	0.000				
S. Africa	0.015	0.000	0.003	0.000				
	Panel B: *Debt flows*							
India	0.005	0.000	0.025	0.000	0.024	0.000	0.000	0.000
Indonesia	0.000	0.000	0.001	0.000				
Korea	0.011	0.000	0.008	0.000				
Brazil	0.002	0.000	0.008	0.000				
Chile	0.007	0.000	0.021	0.000				
Bulgaria	0.000	0.000	0.000	0.000				
Czech R.	0.049	0.000	0.083	0.000				
Poland	0.000	0.000	0.000	0.000				
S. Africa	0.000	0.000	0.000	0.000				
	Panel C: *Stock market returns*							
India	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000
Indonesia	0.000	0.000	0.001	0.000				
Korea	0.000	0.000	0.001	0.000				
Brazil	0.000	0.000	0.000	0.000				
Chile	0.000	0.000	0.001	0.000				
Bulgaria	0.001	0.000	0.004	0.000				
Czech R.	0.000	0.000	0.003	0.000				
Poland	0.008	0.000	0.042	0.000				
S. Africa	0.001	0.000	0.006	0.000				

Notes: This table reports the p-values of unit root tests. ADF, PP, LLC and IPS denote the Augmented Dickey-Fuller, Phillips-Perron, Levin-Lin-Chu, and Im- Pesaran-Shin test, respectively.

Table 1b: Summary Statistics

	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
				Panel A: *Equity flows*			
India	0.076	0.065	0.569	-0.364	0.149	0.502	4.173
Indonesia	0.020	0.030	0.268	-0.794	0.114	-4.443	32.177
Korea	0.011	0.031	0.689	-1.039	0.273	-0.611	4.541
Brazil	0.072	0.038	0.872	-0.434	0.158	2.226	12.442
Chile	0.083	0.052	0.977	-0.231	0.150	2.265	12.507
Bulgaria	0.007	-0.002	0.450	-0.196	0.069	3.040	19.529
Czech R.	-0.012	0.000	0.346	-0.744	0.111	-2.203	16.301
Poland	0.032	0.024	0.506	-0.458	0.123	0.258	5.993
S. Africa	0.065	0.040	0.817	-0.976	0.276	0.073	4.144
All	0.039	0.022	0.977	-1.039	0.174	0.061	9.725
				Panel B: *Debt flows*			
India	0.023	0.015	0.236	-0.294	0.073	-0.072	5.206
Indonesia	0.067	0.072	0.377	-0.434	0.125	-0.385	4.298
Korea	0.126	0.119	1.091	-0.787	0.260	0.289	4.458
Brazil	0.054	0.062	0.425	-0.588	0.177	-0.825	4.300
Chile	0.136	0.053	1.444	-0.488	0.297	1.201	5.769
Bulgaria	0.031	-0.020	3.673	-1.880	0.575	3.630	22.719
Czech R.	0.218	0.104	7.087	-2.784	0.847	4.045	33.675
Poland	0.130	0.086	1.618	-0.764	0.386	0.739	5.089
S. Africa	0.076	0.071	0.849	-0.624	0.289	0.126	2.959
All	0.096	0.044	7.087	-2.784	0.410	5.514	82.275
				Panel C: *Stock market returns*			
India	1.051	1.986	19.307	-27.887	5.731	-0.881	7.672
Indonesia	1.148	1.842	15.955	-33.001	5.439	-1.634	12.745
Korea	0.589	0.927	14.779	-18.546	4.438	-0.852	5.882
Brazil	0.670	1.022	18.118	-28.251	6.035	-0.757	5.824
Chile	0.661	0.908	12.257	-13.471	4.018	-0.599	4.175
Bulgaria	-0.033	0.222	20.712	-43.236	7.790	-1.811	12.826
Czech R.	-0.063	0.587	19.033	-31.239	5.575	-1.251	10.211
Poland	0.569	1.513	15.010	-23.478	5.296	-1.027	6.144
S. Africa	0.966	1.522	7.182	-19.944	3.830	-1.512	8.282
All	0.618	1.168	20.712	-43.236	5.467	-1.411	11.848

Notes: This table reports the descriptive statistics for the equity and debt flow data as well as the stock market returns of nine emerging economies in the sample.

Table 1c: Misspecification tests.

Panel A: Conditional mean misspecification tests					
$R_{i,t} = \gamma_{i,0} + \gamma_1 R_{Wt} + \gamma_2 Debt_{i,t} + \gamma_3 Equity_{i,t} + u_{i,t}$					
Individual Effects: $H_0 : \gamma_{i,0} = \gamma_0$		0.968(0.459)	Individual Effects with HAC		0.903(0.513)
Serial Correlation	$H_0 : \rho(1) = 0$	$H_0 : \rho(2) = 0$	$H_0 : \rho(3) = 0$		
	12.99***	-3.407***	1.797*		
	(0.000)	(0.000)	(0.073)		
$R_{i,t} = \gamma_{i,0} + \gamma_1 Debt_{i,t} + \gamma_2 Equity_{i,t} + u_{i,t}$					
Individual Effects: $H_0 : \gamma_{i,0} = \gamma_0$		0.685 (0.705)	Individual Effects with HAC		0.703 (0.689)
Serial Correlation	$H_0 : \rho(1) = 0$	$H_0 : \rho(2) = 0$	$H_0 : \rho(3) = 0$		
	14.300***	-4.805***	6.249***		
	(0.000)	(0.000)	(0.000)		
Panel B: Conditional variance-covariance misspecification tests					
$R_{i,t} = \gamma_{i,0} + \gamma_1 R_{Wt} + \gamma_2 Debt_{i,t} + \gamma_3 Equity_{i,t} + u_{i,t}$					
Cross-sectional independence		31.032***			
		(0.000)			
ARCH effects					
$u^2_{i,t-1}$	$u^2_{i,t-2}$	$u^2_{i,t-3}$	$u_{i,t-1}u_{i,t-2}$	$u_{i,t-1}u_{i,t-3}$	$u_{i,t-2}u_{i,t-3}$
11.350***	-2.215**	3.583***	-2.827***	0.019	0.049
(0.000)	(0.027)	(0.000)	(0.005)	(0.985)	(0.961)
Individual effects in variance		2.372**			
$H_0 : k_i = k$		(0.016)			
$R_{i,t} = \gamma_{i,0} + \gamma_1 Debt_{i,t} + \gamma_2 Equity_{i,t} + u_{i,t}$					
Cross-sectional independence		38.199***			
		(0.000)			
ARCH effects					
$u^2_{i,t-1}$	$u^2_{i,t-2}$	$u^2_{i,t-3}$	$u_{i,t-1}u_{i,t-2}$	$u_{i,t-1}u_{i,t-3}$	$u_{i,t-2}u_{i,t-3}$
9.097***	0.097	2.452**	-2.381**	2.811***	-1.988**
(0.000)	(0.923)	(0.014)	(0.017)	(0.005)	(0.047)
Individual effects in variance		1.491			
$H_0 : k_i = k$		(0.156)			

***Notes*: Panel A** reports the results of the misspecification tests for the conditional mean. *Individual effects* test for the presence of individual homogeneity in the conditional mean (we report the value of the F-test).*Individual effects with HAC* test for the presence of individual homogeneity using a Wald test based on HAC standard errors. Serial correlation refers to Wooldridge's (2002) test for the presence of serial dependence in the residuals of the conditional mean (we report the values of the t-tests). **Panel B** presents the results of the misspecification tests for the conditional variance and covariance. *Cross-sectional independence* refers to Pesaran's (2004) CD test for the presence of cross-sectional independence (we report the value of the test statistic). *ARCH effects* refer to an AR(3) model of squared residuals and cross products of lagged residuals (we report the t-test values). *Individual effects in variance* test for the presence of individual homogeneity in the conditional variance (we report the F-test value). *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table 2: The effect of fund flows on stock market return and risk (*whole sample results*).

Models	Fixed effects (A)	Pooled regression (B)	Fixed effects (C)	Pooled regression (D)
Panel A: Conditional mean specification				
Constant	-0.122*	-0.079	0.137	0.247***
	(0.056)	(0.347)	(0.524)	(0.000)
$Debt_{i,t}$	-0.090***	-0.126***	-0.072**	-0.114***
	(0.000)	(0.000)	(0.029)	(0.000)
$Equity_{i,t}$	0.470	0.659	0.585	0.811***
	(0.225)	(0.152)	(0.169)	(0.001)
R_{wt}	0.962***	0.985***		
	(0.000)	(0.000)		
Panel B: Conditional variance specification				
India	2.996***	2.991***	3.478***	3.441***
	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	2.334***	2.330***	2.914***	2.861***
	(0.000)	(0.000)	(0.000)	(0.000)
Korea	1.970***	2.004***	2.164***	2.132***
	(0.000)	(0.000)	(0.000)	(0.000)
Brazil	3.854***	3.858***	4.586***	4.675***
	(0.000)	(0.000)	(0.000)	(0.000)
Chile	2.134***	2.203***	1.879***	1.904***
	(0.000)	(0.000)	(0.001)	(0.000)
Bulgaria	3.577***	3.418***	3.419***	3.299***
	(0.000)	(0.000)	(0.000)	(0.004)
Czech Rep.	2.511***	2.541***	3.478***	3.581***
	(0.000)	(0.000)	(0.000)	(0.000)
Poland	2.847***	2.846***	3.515***	3.515***
	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	1.734***	1.795***	1.831***	1.814***
	(0.000)	(0.000)	(0.000)	(0.000)
GARCH	0.798***	0.792***	0.789***	0.785***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	0.064***	0.069***	0.084***	0.089***
	(0.000)	(0.000)	(0.000)	(0.000)
$Debt_{i,t}$	-0.679***	-0.659***	-0.833***	-0.822***
	(0.000)	(0.000)	(0.000)	(0.000)
$Equity_{i,t}$	-0.259***	-0.309	-0.195	-0.273
	(0.000)	(0.489)	(0.807)	(0.438)
R_{wt}	-0.813***	-0.877***		
	(0.000)	(0.000)		
Log-likelihood	-33499000	-33532000	-33780000	-33798000

***Notes*:** This table presents the estimation results for the conditional mean and variance-covariance equations described in Equations (1)-(3).**Panels A and B** in the table present the findings for the conditional mean and variance equations, respectively. The conditional mean equation for models A and B is described in Equation (1) where $R_{w,t}$ is the MSCI world stock market index return for month *t* and $Debt_{i,t}$ ($Equity_{i,t}$) are the country-specific debt (equity) flows. The conditional variance and covariance of each model is given in Equations (2)-(3). Models C and D have the same setup as Models A and B except that the world market return ($R_{w,t}$) is excluded from the equations. Models A and Care estimated as a panel regression with cross-sectional fixed effects, while models B and Dare estimated as a pooled regression. *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table 3: The effect of fund flows on stock market return and risk (*sub-period results*).

	Subperiod 1 (2/2005-12/2008)		**Subperiod 2** (1/2009-3/2017)	
Models	Fixed effects	Pooled regression	Fixed effects	Pooled regression
Panel A: Conditional mean specification				
Constant	0.0296	-0.099	-0.399***	-0.393***
	(0.964)	(0.113)	(0.000)	(0.000)
R_{wt}	1.272***	1.302***	0.749***	0.788***
	(0.000)	(0.000)	(0.000)	(0.000)
$Debt_{i,t}$	0.393	0.383*	-0.096***	-0.132***
	(0.169)	(0.071)	(0.000)	(0.000)
$Equity_{i,t}$	-0.167	0.854***	1.889***	2.028***
	(0.699)	(0.000)	(0.000)	(0.000)
Panel B: Conditional variance specification				
India	8.091***	8.509***	2.302***	2.399***
	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	7.648***	8.074***	1.851***	1.882***
	(0.000)	(0.000)	(0.000)	(0.000)
Korea	4.921***	4.975***	1.291***	1.330***
	(0.000)	(0.000)	(0.000)	(0.000)
Brazil	7.066***	7.090***	3.902**	3.932***
	(0.000)	(0.000)	(0.010)	(0.000)
Chile	2.839***	3.257***	2.012***	2.020***
	(0.000)	(0.000)	(0.001)	(0.000)
Bulgaria	6.657***	6.726***	3.250***	3.271***
	(0.000)	(0.000)	(0.000)	(0.000)
Czech Rep.	4.561***	4.122***	3.206***	3.234***
	(0.000)	(0.000)	(0.000)	(0.000)
Poland	6.835***	6.853***	2.661***	2.615***
	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	3.076***	3.149***	1.421***	1.461***
	(0.000)	(0.000)	(0.000)	(0.000)
GARCH	0.727***	0.680***	0.753***	0.743***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	0.058	0.078***	0.069***	0.069***
	(0.252)	(0.000)	(0.000)	(0.000)
R_{wt}	-1.819***	-1.749***	-0.101***	-0.093***
	(0.000)	(0.000)	(0.000)	(0.000)
$Debt_{i,t}$	0.057	0.039***	-1.003***	-0.939***
	(0.928)	(0.004)	(0.000)	(0.000)
$Equity_{i,t}$	-0.221	-0.216***	-0.209***	-0.212***
	(0.837)	(0.000)	(0.000)	(0.000)
Log-likelihood	-10993000	-11016000	-21966000	-21985000

***Notes*:** This table presents the estimation results for the conditional mean and variance-covariance equations described in Equations (1)-(3).**Panels A and B** in the table present the findings for the conditional mean and variance equations, respectively. $R_{w,t}$ is the MSCI world stock market index return for month *t* and $Debt_{i,t}$ ($Equity_{i,t}$) are the country-specific debt (equity) flows. Fixed effects refer to panel regressions with cross-sectional fixed effects while the alternative model is estimated as a pooled regression. The first (second) sub-period covers 2/2005-12/2008 and 1/2009-3/2017, respectively. *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table 4: The effect of world market volatility.

Models	Fixed effects (A)	Pooled regression (B)	Fixed effects (C)	Pooled regression (D)
Panel A: Conditional mean specification				
Constant	-0.125	-0.109***	0.076	0.228
	(0.222)	(0.000)	(0.805)	(0.444)
$Debt_{i,t}$	-0.078**	-0.106***	-0.089	-0.114
	(0.044)	(0.000)	(0.334)	(0.183)
$Equity_{i,t}$	0.408	0.666***	0.647	0.590
	(0.509)	(0.006)	(0.158)	(0.156)
R_{wt}	1.002***	1.016***		
	(0.001)	(0.000)		
VR_{wt}	-0.019	-0.013	1.360	1.476
	(0.717)	(0.721)	(0.832)	(0.805)
Panel B: Conditional variance specification				
India	4.497***	4.476***	3.417***	3.512***
	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	3.654***	3.594***	2.862***	2.809***
	(0.000)	(0.000)	(0.000)	(0.000)
Korea	2.461***	2.484***	2.160***	2.223***
	(0.000)	(0.000)	(0.000)	(0.000)
Brazil	5.954***	5.877***	4.522***	4.851***
	(0.000)	(0.000)	(0.000)	(0.000)
Chile	2.785***	2.834***	1.869***	1.914***
	(0.001)	(0.000)	(0.000)	(0.000)
Bulgaria	5.722***	5.545***	3.389***	3.375***
	(0.000)	(0.000)	(0.000)	(0.000)
Czech Rep.	3.586***	3.582***	3.419***	3.541***
	(0.000)	(0.000)	(0.000)	(0.000)
Poland	3.809***	3.878***	3.499***	3.522***
	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	2.264***	2.289***	1.841***	1.762***
	(0.000)	(0.000)	(0.000)	(0.000)
GARCH	0.688***	0.698***	0.791***	0.785***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	0.066***	0.064***	0.084***	0.087***
	(0.000)	(0.000)	(0.000)	(0.000)
R_{wt}	-0.841***	-0.890***		
	(0.000)	(0.000)		
$Debt_{i,t}$	-0.700***	-0.695***	-0.829***	-0.804***
	(0.000)	(0.000)	(0.000)	(0.000)
$Equity_{i,t}$	-0.313	-0.356**	-0.196	-0.261
	(0.914)	(0.013)	(0.801)	(0.742)
VR_{wt}	0.159***	0.142***	0.047	0.059
	(0.000)	(0.000)	(0.995)	(0.993)
Log-likelihood	-33521000	-33532000	-33774000	-33804000

***Notes*:** This table presents the estimation results for the conditional mean and variance-covariance equations described in Equations (3), (8a) and (8b) where VR_{wt} is a proxy for the world stock market volatility. **Panels A and B** in the table present the findings for the conditional mean and variance equations, respectively. Models C and D have the same setup as Models A and B except that the world market return ($R_{w,t}$) is excluded from the equations. Models A and C are estimated as a panel regression with cross-sectional fixed effects, while models B and Dare estimated as a pooled regression. *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table 5: Asymmetric effects in conditional variance.

Models	Fixed effects (A)	Pooled regression (B)	Fixed effects (C)	Pooled regression (D)
Exhibit A: conditional mean specification				
Constant	-0.138	-0.132***	-0.054	0.063
	(0.572)	(0.000)	(0.820)	(0.794)
$Debt_{i,t}$	-0.102*	-0.104***	-0.037	-0.069
	(0.073)	(0.000)	(0.665)	(0.438)
$Equity_{i,t}$	0.421	0.625*	0.730*	0.792*
	(0.313)	(0.071)	(0.077)	(0.054)
R_{wt}	0.977***	1.032***		
	(0.000)	(0.000)		
Exhibit B: conditional variance specification				
India	2.946***	2.894***	3.696***	3.746***
	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	2.304***	2.295***	3.039***	3.079***
	(0.000)	(0.000)	(0.000)	(0.000)
Korea	1.946***	1.946***	2.357***	2.328***
	(0.000)	(0.000)	(0.000)	(0.000)
Brazil	3.823***	3.806***	4.720***	4.834***
	(0.000)	(0.000)	(0.000)	(0.000)
Chile	2.157***	2.225***	1.998***	2.037***
	(0.000)	(0.000)	(0.001)	(0.000)
Bulgaria	3.612***	3.448***	3.801***	3.625***
	(0.000)	(0.000)	(0.000)	(0.004)
Czech Rep.	2.492***	2.417***	3.548***	3.573***
	(0.000)	(0.000)	(0.000)	(0.000)
Poland	2.823***	2.743***	3.659***	3.611***
	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	1.734***	1.751***	1.940***	1.930***
	(0.000)	(0.000)	(0.000)	(0.000)
GARCH	0.793***	0.802***	0.782***	0.779***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	0.062***	0.056***	0.050**	0.053**
	(0.005)	(0.000)	(0.023)	(0.019)
Asymmetric effect	0.009	0.012***	0.062**	0.058*
	(0.747)	(0.000)	(0.049)	(0.070)
$Debt_{i,t}$	-0.665***	-0.646***	-0.822***	-0.803***
	(0.000)	(0.000)	(0.000)	(0.000)
$Equity_{i,t}$	-0.309	-0.368***	-0.326	-0.427
	(0.708)	(0.000)	(0.686)	(0.587)
R_{wt}	-0.819***	-0.867***		
	(0.000)	(0.000)		
Log-likelihood	-33519000	-33516000	-33765000	-33786000

***Notes*:** This table presents the estimation results for the asymmetric panel GARCH model described in Equation (8c) where the asymmetric effect is represented by an indicator function that takes on the value 1 if $u_{i,t-1} < 0$ and 0 otherwise. Models C and D have the same setup as Models A and B except that the world market return ($R_{w,t}$) is excluded from the equations. Models A and Care estimated as a panel regression with cross-sectional fixed effects, while models B and Dare estimated as a pooled regression. *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table 6: Portfolio flows and idiosyncratic risk.

Dependent Variable	$IV_{i,t} = \varepsilon_{i,t}^2$		$IV_{i,t} = \lvert\varepsilon_{i,t}\rvert$	
Models	(A)	(B)	(C)	(D)
Panel A: Conditional mean specification				
Constant	1.269***	0.905***	2.452***	2.582***
	(0.000)	(0.000)	(0.000)	(0.000)
$Debt_{i,t}$	-0.184	-0.013*	-0.054***	-0.085***
	(0.664)	(0.073)	(0.000)	(0.003)
$Equity_{i,t}$	-0.034	-0.264***	0.185	-0.291
	(0.811)	(0.000)	(0.446)	(0.345)
R_{wt}	-0.484***		-0.099***	
	(0.000)		(0.000)	
Panel B: Conditional variance specification				
India	3.737**	3.331***	2.066***	2.138***
	(0.049)	(0.000)	(0.000)	(0.000)
Indonesia	2.409***	4.090***	1.679***	2.010***
	(0.000)	(0.000)	(0.000)	(0.000)
Korea	0.821***	0.606***	1.006***	0.997***
	(0.000)	(0.000)	(0.000)	(0.000)
Brazil	3.401***	3.376***	2.615***	2.767***
	(0.000)	(0.000)	(0.000)	(0.000)
Chile	1.09***	1.089***	1.194***	1.248***
	(0.000)	(0.000)	(0.000)	(0.000)
Bulgaria	18.474**	7.875***	3.174***	3.473***
	(0.012)	(0.000)	(0.000)	(0.000)
Czech Rep.	2.027***	1.953***	1.566***	1.569***
	(0.000)	(0.000)	(0.000)	(0.000)
Poland	1.256***	1.355***	1.402***	1.409***
	(0.000)	(0.000)	(0.001)	(0.001)
South Africa	0.503***	0.467***	0.764***	0.816***
	(0.000)	(0.000)	(0.000)	(0.000)
GARCH	0.469***	0.645***	0.720***	0.673***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	0.361***	0.178***	0.083***	0.089***
	(0.000)	(0.000)	(0.000)	(0.000)
$Debt_{i,t}$	0.057	-0.269***	-0.432***	-0.442***
	(0.102)	(0.000)	(0.000)	(0.000)
$Equity_{i,t}$	-0.016	-0.755***	-0.345***	-0.336
	(0.795)	(0.000)	(0.000)	(0.485)
R_{wt}	-0.242***		-0.307***	
	(0.000)		(0.000)	
Log-likelihood	-28972000	-29053000	-29194000	-29366000

Notes**:** This table presents the estimation results for the conditional mean and variance-covariance equations described in Equations (10)-(13)where $\varepsilon_{i,t}$ are the residuals in panel form obtained from Equation (9) and idiosyncratic volatility is computed as $IV_{i,t} = \varepsilon_{i,t}^2$ (Models A and B) and $IV_{i,t} = \lvert\varepsilon_{i,t}\rvert$ (Models C and D). **Panels A and B** present the findings for the conditional mean and variance equations, respectively. Models B and D have the same setup as Models A and C except that the world market return ($R_{w,t}$) is excluded from the equations. *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Appendix.

Table A1: The effect of fund flows after controlling for market liquidity.

Models	Fixed effects (A)	Pooled regression (B)	Fixed effects (C)	Pooled regression (D)
Panel A: Conditional mean specification				
Constant	-0.119*	-0.078	0.204***	0.308***
	(0.000)	(0.234)	(0.000)	(0.000)
$Debt_{i,t}$	-0.095***	-0.122***	-0.096**	-0.117***
	(0.000)	(0.000)	(0.013)	(0.000)
$Equity_{i,t}$	0.527	0.565	0.597***	0.687***
	(0.403)	(0.740)	(0.001)	(0.007)
R_{wt}	0.973***	1.028***		
	(0.000)	(0.000)		
$LIQ_{i,t}$	0.664	0.327	1.587**	1.239
	(0.516)	(0.899)	(0.013)	(0.124)
Panel B: Conditional variance specification				
India	2.885***	2.789***	3.369***	3.403***
	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	2.289***	2.186***	2.915***	2.839***
	(0.000)	(0.000)	(0.000)	(0.000)
Korea	1.977***	1.984***	2.169***	2.212***
	(0.000)	(0.000)	(0.000)	(0.000)
Brazil	3.905***	3.769***	4.757***	4.829***
	(0.000)	(0.000)	(0.000)	(0.000)
Chile	2.183***	2.216***	1.911***	1.935***
	(0.001)	(0.000)	(0.000)	(0.000)
Bulgaria	3.581***	3.336*	3.405***	3.352***
	(0.000)	(0.061)	(0.000)	(0.000)
Czech Rep.	2.498***	2.429***	3.565***	3.575***
	(0.000)	(0.000)	(0.000)	(0.000)
Poland	2.883***	2.785***	3.595***	3.542***
	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	1.748***	1.747***	1.797***	1.770***
	(0.000)	(0.003)	(0.000)	(0.000)
GARCH	0.787***	0.802***	0.786***	0.783***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	0.072***	0.064***	0.085***	0.086***
	(0.000)	(0.000)	(0.000)	(0.000)
R_{wt}	-0.829***	-0.889***		
	(0.000)	(0.000)		
$Debt_{i,t}$	-0.657***	-0.659***	-0.847***	-0.822***
	(0.000)	(0.000)	(0.000)	(0.000)
$Equity_{i,t}$	-0.236	-0.310*	-0.145	-0.227
	(0.164)	(0.080)	(0.120)	(0.378)
$LIQ_{i,t}$	-0.358***	-0.355**	-0.408	-0.393
	(0.000)	(0.016)	(0.146)	(0.312)
Log-likelihood	- 33487000	- 33511000	- 33747000	- 33779000

***Notes*:** This table presents the estimation results for the conditional mean and variance-covariance equations described in Equations (3), (8a) and (8b) where LIQ_t is a proxy for liquidity along the lines of Vagias and van Dijk (2011) and Karolyi et. al (2012) based on the illiquidity measure of Amihud (2002). **Panels A and B** present the findings for the conditional mean and variance equations, respectively. Models C and D have the same setup as Models A and B except that the world market return ($R_{w,t}$) is excluded from the equations. Models A and Care estimated as a panel regression with cross-sectional fixed effects, while models B and D are estimated as a pooled regression. *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table A2. Joint and individual significance of the instrumental variables.

Panel A: Instruments for debt flows					
$Debt_{i,t} = \alpha_{i,0} + \sum_{j=0}^{5} \beta_j dDebt_{i,t-j} + u_{i,t}$					
Instrument relevance: $H_0: \beta_0 = \beta_1 = ... = \beta_5 = 0$		1337.18*** (0.000)			
$H_0: \beta_0 = 0$	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 0$	$H_0: \beta_3 = 0$	$H_0: \beta_4 = 0$	$H_0: \beta_5 = 0$
7203.86***	2838.92***	1369.84***	902.333***	485.11***	170.626***
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Debt_{i,t} = \alpha_{i,0} + \sum_{j=0}^{5} \beta_j dDebt_{i,t-j} + \gamma_1 R_{Wt} + u_{i,t}$					
Instrument relevance: $H_0: \beta_0 = \beta_1 = ... = \beta_5 = 0$		1320.58*** (0.000)			
$H_0: \beta_0 = 0$	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 0$	$H_0: \beta_3 = 0$	$H_0: \beta_4 = 0$	$H_0: \beta_5 = 0$
7115.56***	2812.44***	1364.6***	900.410***	484.305***	170.200***
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Instruments for equity flows					
$Equity_{i,t} = \alpha_{i,0} + \sum_{j=0}^{5} \beta_j dEquity_{i,t-j} + u_{i,t}$					
Instrument relevance: $H_0: \beta_0 = \beta_1 = ... = \beta_5 = 0$		396.59*** (0.000)			
$H_0: \beta_0 = 0$	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 0$	$H_0: \beta_3 = 0$	$H_0: \beta_4 = 0$	$H_0: \beta_5 = 0$
2249.400***	1099.98***	662.423***	439.251***	242.711***	101.355***
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Equity_{i,t} = \alpha_{i,0} + \sum_{j=0}^{5} \beta_j dEquity_{i,t-j} + \gamma_1 R_{Wt} + u_{i,t}$					
Instrument relevance: $H_0: \beta_0 = \beta_1 = ... = \beta_5 = 0$		365.908*** (0.000)			
$H_0: \beta_0 = 0$	$H_0: \beta_1 = 0$	$H_0: \beta_2 = 0$	$H_0: \beta_3 = 0$	$H_0: \beta_4 = 0$	$H_0: \beta_5 = 0$
2079.970***	1035.66***	639.728***	423.513***	228.994***	95.982***
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

***Notes*:** This table presents the results of F-statistics for joint and individual significance of the instrumental variables. Panels A and B present the findings for the auxiliary regressions of debt and equity flows on their instruments, respectively. We report the test results for the main auxiliary regression as well as a second model where we control for world stock market index returns $R_{W,t}$. Each auxiliary model is a panel fixed-effects regression of portfolio flows on the differenced and lagged differenced portfolio flows. p-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.

Table A3: Models estimated with instrumental variables.

Models	(A)	(B)	(C)	(D)	(E)	(F)
			Panel A: Conditional mean specification			
Constant	-0.167***	0.344***	-0.241	-0.178***	-0.009	0.031***
	(0.000)	(0.000)	(0.354)	(0.000)	(0.981)	(0.000)
$Debt_{i,t}$	-0.129***	-0.175***	-0.158	-0.171**	-0.132	-0.145***
	(0.000)	(0.000)	(0.114)	(0.029)	(0.569)	(0.000)
$Equity_{i,t}$	0.605	0.630*	1.209**	1.110**	0.329	0.524
	(0.209)	(0.057)	(0.022)	(0.042)	(0.693)	(0.120)
R_{wt}	0.963***		0.994***		0.939***	
	(0.000)		(0.000)		(0.000)	
$Credit_{i,t}$			-0.018	0.077***		
			(0.896)	(0.000)		
VR_{wt}					-0.023	0.045***
					(0.718)	(0.000)
			Panel B: Conditional variance specification			
India	2.313***	3.093***	2.085***	2.577***	3.164***	3.354***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indonesia	1.841***	2.071***	1.404***	1.789***	2.654***	2.811***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
Korea	1.449***	1.816***	3.383***	3.807***	1.887***	2.193***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brazil	3.022	3.802***	2.671***	3.353***	4.255	4.442***
	(0.114)	(0.000)	(0.000)	(0.000)	(0.114)	(0.000)
Chile	1.619***	1.714***	2.746***	2.895***	2.058***	1.816***
	(0.003)	(0.00)	(0.000)	(0.000)	(0.003)	(0.00)
Bulgaria	2.728**	3.606***	2.355***	2.742***	3.817**	3.453***
	(0.015)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)
Czech Rep.	1.800***	2.614***	2.342***	3.086***	2.435***	3.327***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Poland	2.106***	2.765***	2.296***	2.979***	2.757***	3.554***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	1.309***	1.566***	1.941***	2.167***	1.726***	1.744***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GARCH	0.826***	0.802***	0.891***	0.869***	0.774***	0.791***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	0.066***	0.087***	0.048***	0.063***	0.065***	0.085***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Debt_{i,t}$	-0.688***	-0.859***	-0.568***	-0.791***	-0.730***	-0.985***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Equity_{i,t}$	0.233	0.015	0.222	0.021	0.231	0.003
	(0.534)	(0.569)	(0.814)	(0.950)	(0.864)	(0.905)
R_{wt}	-0.727***		-0.575***		-0.802***	
	(0.000)		(0.000)		(0.000)	
$Credit_{i,t}$			-1.588***	-1.653***		
			(0.000)	(0.000)		
VR_{wt}					0.065	0.000***
					(0.319)	(0.000)
Log-likelihood	- 33497000	- 33781000	- 33435000	-33732000	- 33517000	- 33755000

***Notes*:** This table presents the estimation results for the conditional mean and variance-covariance equations described in Equations (1)-(3). **Panels A and B** present the findings for the conditional mean and variance equations, respectively. $R_{w,t}$ is the MSCI world stock market index return for month *t* and $Debt_{i,t}$ ($Equity_{i,t}$) are the instrumented country-specific debt (equity) flows. $Credit_{i,t}$ are the country-specific bank credit flows and VR_{wt} is a proxy for the world stock market volatility. The conditional variance and covariance of each model is given in Equations (2)-(3). All models are estimated as a panel regression with cross-sectional fixed effects. *p*-values are reported in parentheses. *, **, and *** indicate significance at 10, 5 and 1 percent levels, respectively.