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RESEARCH ARTICLE

Equity flows, stock returns and exchange rates

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Abstract

We explore the effects of equity flows between U.S. and U.K. investors upon equity and exchange rate returns within a unified empirical framework on the basis of a trivariate vector autoregressive system that incorporates mean and volatility spillovers and allows for dynamic conditional correlations. Our findings are as follows: First, we reveal strong evidence of volatility spillovers across equity returns, exchange rate returns, and equity flows. Second, we find strong evidence that U.K. investors rebalance their portfolios by engaging in a positive feedback trading known in the literature as "trend chasing." Third, we document strong dynamic effects from net flows to equity returns, illustrating a trading rule that portfolios are dynamically adjusted over a short-run horizon influencing changes in stock returns. Last, correlation uncertainty appears to be reduced from the start of the 1990s onwards.

KEYWORDS

dynamic correlations, equity returns, exchange rates, net flows, trading, volatility

1 | INTRODUCTION

Cross border capital flows have attracted attention in the literature due to their significant increase over the recent period (Caporale, Ali, & Spagnolo, 2015). The present paper deals with equity flow movements between the United States and the United Kingdom, using a unified framework for the joint determination of equity flows, exchange rates, and equity returns. A vector autoregressive (VAR) system is employed, with explicit multivariate generalized autoregressive conditional heteroskedasticity (GARCH) modeling of conditional variances, volatility spillovers, and allowance for dynamic conditional correlations (DCCs) among the variables in hand.

The paper's contribution is twofold. First, we explicitly model dynamic volatility spillovers between these variables. Incorporating conditional variance interactions is important for two reasons. According to Hau and Rey (2006), the typical foreign equity investor holds currency risk and equity risk as a bundle (page 276). As markets are not complete (in which investors could swap and eliminate risk), exposure to risk implies that the international investor cares about both the volatilities of exchange rate and equity returns and for the correlation structure of exchange rates and equity returns. Another reason is that explicit modeling of volatility linkages helps us measure more accurately correlations, which constitute an important decision variable for international investors. Importantly, using a trivariate vector autoregressive-generalized autoregressive conditional heteroskedasticity (VAR-GARCH) framework, we simultaneously explore mean spillovers between net equity flows, exchange rate returns, and equity returns and thus, extend previous results from regression and VAR approaches (Ahearne, Griever, & Warnock, 2004; Brennan & Cao, 1997; Froot, O'Connell, & Seasholes, 2001; Hau & Rey, 2006). To our knowledge, this is the first study to look at both mean and volatility spillovers.

Second, in our trivariate VAR-GARCH model, we allow for DCCs. According to Hau and Rey (2004), conditional correlations between exchange rate returns, equity returns, and equity flows are important and carry implications regarding portfolio rebalancing. Importantly, the dynamic time-varying conditional correlations obtained are free of any mean and volatility spillovers as the latter have been explicitly modeled. Our approach extends Hau and Rey's (2006) time-invariant unconditional correlations, by showing that the average correlation coefficient for the net flows—exchange rate changes and for the returns differential—exchange rate changes are lower than those found by Hau and Rey (2006). Dynamic correlations and "correlation uncertainty" are found to be reduced from the start of the 1990s to present.

The rest of the paper is as follows. Section 2 presents the econometric methodology. Section 3 outlines the data. Section 4 discusses the empirical results. Section 5 concludes.

2 | ECONOMETRIC METHODOLOGY: THE TRIVARIATE VAR-GARCH-DCC MODEL

Let Y_t, Z_t, and X_t be the net equity flows, returns differential, and exchange rate returns, respectively, $v_t \equiv [Y_t, Z_t, X_t]^{'}$ be a 3X1 vector containing the 3 variables, and $\xi_t \equiv [X_t, Z_t, Y_t]^{'}$. Assuming stationarity for all 3 variables, a common representation for the conditional mean equation with mean spillovers is the following VAR:

$$A(L)v_t = \boldsymbol{\delta}\xi_{t-1} + \varepsilon_t, \quad \text{where} \quad \varepsilon_t/\Omega_{t-1} \tag{1}$$

where $A(L)$ is a polynomial matrix in the lag operator L, Ω_{t-1} is the information set at time t-1, $\boldsymbol{\delta}$ is a matrix of coefficients for the cross-market mean spillovers, and $\varepsilon_t = [\varepsilon_{Y,t}, \varepsilon_{Z,t}, \varepsilon_{X,t}]^{'}$ is a vector of innovations, which, conditional upon Ω_{t-1}, has a conditional variance–covariance matrix $H_t \equiv \{h_i\}_t \forall i$, $\forall t = 1, \ldots T$. The GARCH component (Engle, 2002) is reflected in the matrix:

$$H_t \equiv D_t R_t Dt \tag{2}$$

where $D_t = diag\left[\sqrt{h_{it}}\right]$ is a diagonal matrix of time varying standard deviations from univariate GARCH models, and $R_t = \{\rho_{ij,t}\}, i,j = Y,Z,X$, which is a time-varying correlation matrix containing DCC coefficients. The time-varying conditional correlation matrix, R_t, is assumed to follow a DCC structure DCC(1,1) in which R_t is written as

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{3}$$

where

$$Q_t = (1 - z_1 - k_1)\overline{Q} + z_1\left(\varepsilon_{t-1}\varepsilon^{'}{}_{t-1}\right) + k_1 Q_{t-1} \tag{4}$$

where $Q_1 \equiv \{q_{ij}\}_t$ is the conditional variance–covariance matrix of residuals with its time-invariant (unconditional) variance–covariance matrix $\overline{Q}$ obtained from Equation 4, and $Q_t^* = diag\left[\sqrt{q_{ii}}\right]$ is a diagonal matrix containing the square root of the diagonal elements of Q_t.

An important feature of our econometric approach is that it filters away any variance spillovers, which is important for the accurate calculation of correlations. Following Ling and McAller (2003), the variance of the individual processes take the form:

$$H_{ii}(t) + \sum_j a_{ij}\left(u_j(t-1)\right)^2 + \sum_j b_{ij} H_{jj}(t-1) \tag{5}$$

which allows large shocks on one variable to affect the variance of the others. In Equation 5, a_{ij} captures the volatility spillover from market j to market i, where i = X, Y, Z, and j = X, Y, Z, and $i \neq j$.

The elements in D_t follow the GARCH(1,1) process:

$$h_{i,t}^2 = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{i,t-1}^2 \qquad i = Y_t, Z_t, X_t \tag{6}$$

The model reflected in Equations 1–6 is a trivariate vector autoregressive-generalized autoregressive conditional heteroskedasticity-dynamic conditional correlation, VAR-GARCH(1,1)-DCC(1,1), model with mean and volatility spillovers.[1] For flexibility, we assume the t-distribution with θ degrees of freedom, with θ being a parameter to be estimated. This model has the important feature that it captures both mean and volatility spillover effects across the three markets and filters away such effects. This is particularly important for the estimation of correlations which, as they are based on the estimation of variances, they do not incorporate any variance spillovers. The so estimated correlations are a better measure of the "pure" correlation, which is free of any common effects.

3 | DATA

The data employed are the portfolio flows data known as Treasury International Capital (TIC) data[2]. They are available on a monthly frequency over the period 1977–2011 and measure transactions in portfolio equities between U.S. and U.K. residents.[3] As any transactions data can be viewed from the perspective of the buyer or the seller, we look at the transactions from the perspective of the U.K. resident who contemplates investing in U.S. equities.[4]

Using this data set, we compute net purchases of U.K. equities by U.S. residents and net purchases of U.S. equities by U.K. residents following Hau and Rey (2006, page 305). Net U.K. equity purchases are defined as the net U.S. purchases of U.K. equities minus net U.K. purchases of U.S. equities. Due to the fact that cross-border equity flows have been constantly growing over the recent period, flows are normalized. The monthly net purchase of U.S. equities is normalized by the monthly total market amount of U.S. equities also provided in the TIC data. Similarly, the monthly net purchase of U.K. stocks is normalized by the monthly total market amount of U.K. stocks.[5] Equity returns are defined as the first log difference of the S&P 500 and the FTSE All-Share indices. Returns differential is defined as the FTSE index returns minus the S&P 500 index returns. The exchange rate is defined as the amount of dollars per 1 Pound sterling, and exchange rate returns are defined as the first difference of the log of the exchange rate over two consecutive months. Exchange rate and stock index data are obtained from Datastream.

Several studies exploring the relationship between equity flows and returns (e.g., Froot et al., 2001) use daily (instead of monthly) proprietary data obtained from various custodian sources. One of the strengths of this data set is that it better captures the timings of the records. However, as stated by Richards (2005), these data are only a partial measure of the flows of foreign (i.e., U.K.) investors, because they relate only to the trades of the custodian, which recorded and provided the data. Another criticism addressed to such daily data is that these data are not the actual trades of foreign investors but are based on contractual settlement dates. Because recent studies (Hau & Rey, 2006; etc.) focused on monthly flows data based on the TIC data, we consider this source and concentrate on the monthly TIC series.[6]

Table 1 reports descriptive statistics for net flows, returns differential, and exchange rate returns. A pictorial representation of the variables is given in Table 1. All three variables are departing from normality on the basis of the Jarque–Bera test. Using the DF-GLS unit root test of Elliott, Rothenberg, and Stock (1996), the null of nonstationarity is strongly rejected for all variables.

4 | EMPIRICAL FINDINGS

4.1 | Linear VAR results

As a benchmark, we consider a linear VAR for the three variables with mean spillovers. The starting point in the empirical analysis is the lag specification in the VAR representation for the conditional means. Using the likelihood ratio test of alternative lag lengths, we tested for 3 vsv 2 lags, and 2 lags versus 1 lag. On the basis of this test, a lag structure of 2 was chosen. Table 2 reports the results. Based on the linear VAR specification, there are no mean spillovers from returns differential to either net flows or exchange rate returns. There exist mean spillovers from net flows to returns differential at lag 2 and from exchange rate returns to returns at lag 1. Finally, there is no evidence of spillovers to exchange rate returns. Thus, the only evidence of spillovers is that documented for the returns differential, which appears to be the "importer" of dynamic effects from exchange rate returns and from net flows.

4.2 | Trivariate VAR-GARCH-DCC results

4.2.1 | Mean spillovers

On the basis of the likelihood ratio test of alternative lag lengths, a lag structure of 2 was chosen. We confirmed that at the chosen lag structure the residuals are free from remaining linearities and nonlinearities (i.e., white).[7] For the maximization of the likelihood function, the BFGS algorithm was employed with heteroscedasticity and misspecification robust standard errors on the basis of the Bollerslev and Wooldridge's (1992) method. The estimation results are reported in Table 3.

Starting with the conditional mean equation for net flows (Y), it can be seen that both autoregressive coefficients of net flows ($\delta_{Y,Y,1}$ and $\delta_{Y,Y,2}$) are both statistically significant. More importantly, the coefficients capturing the spillover (lagged) effect from returns differential (Z) at lags 1 and 2, $\delta_{Y,Z,1}$ and $\delta_{Y,Z,2}$, respectively, are both strongly statistically significant. This suggests that there exist dynamic mean spillovers from returns differentials to net flows. Thus, allowing for multivariate GARCH modeling reveals evidence of mean spillovers, which would not had been traced if GARCH modeling was not allowed for (Table 2).

This mean spillover effect from returns differentials to net flows is interpreted as evidence of portfolio rebalancing due to equity price shocks and is in line with "Hypothesis 1" in Hau and Rey (2004).[8] The positive spillover coefficient suggests that if the U.K. stock returns are higher than the U.S. returns (and the returns differential is positive), the net purchase of U.K. stock is higher than the net purchase of U.S. stock in the next two subsequent months. From the perspective of a U.S. investor, if the U.S. stock returns are relatively lower than the U.K. returns, U.S. residents sell U.K. stock and thus reduce their exposure to foreign stock. According to Hau and Rey (2004), this is a manifestation of a portfolio rebalancing channel due to equity price shocks and is justified by imperfect exchange risk trading.[9] As $\delta_{Y,Z,2}$ is also significant (and positive), we conjecture that the dynamic effect of stock returns differential on net flows is "persistent." This finding suggests that U.K. investors rebalance their portfolios by engaging in a positive feedback trading known in the literature as "trend chasing." Positive feedback trading means that an increase in this month's returns differential leads to an increase in net flows over the next 2 months. Portfolio rebalancing and trend chasing would not had been revealed if multivariate GARCH modeling was not allowed for.

The coefficient capturing the spillover effect from the exchange rate returns to net flows at lag 1 ($\delta_{Y,X,1}$) is strongly statistically significant and negative. As the exchange rate is defined as the amount of U.S. dollars per 1 Pound, an increase in the value (appreciation) of the pound causes a negative effect upon net flows, that is, yields the net purchase of U.S. stocks to be higher than the net purchase of U.K. stocks, in the subsequent month. This is consistent with the fact that an appreciation of the pound against the U.S. dollar increases the purchasing power of U.K. residents in terms of U.S. $-denominated stock, which in turn triggers a swift of attention to U.S. stock. Overall, net flows are a recipient of significant dynamic spillovers from the returns differential and the exchange rate returns. This implies that appropriate

TABLE 1 Descriptive statistics

	Mean	Standard deviation	JB	DF-GLS Unit Root test
Net flows (Y)	−0.017	0.033	28,293.0	−5.22[a]
Returns differential (Z)	0.000	0.063	44.68	−20.30[a]
Exchange rate returns (X)	−0.0003	0.025	55.07	−14.37[a]

Note. JB stands for the Jarque–Bera test statistic for normality. The DF-GLS unit rot test is the test of Elliott et al. (1996). The 5% critical value is −1.9411.

[a]Rejection of the null of nonstationarity.

TABLE 2 Linear VAR(2) with mean spillovers

	Dependent variable: (Y = net flows)	**Dependent variable: (Z = returns differential)**	**Dependent variable: (X = exchange rate return)**
μ_Y	−0.009* (−5.25)		
$\delta_{Y,Y,1}$	0.324* (6.65)		
$\delta_{Y,Y,2}$	0.140* (2.89)		
	Mean spillovers from Z to Y		
$\delta_{Y,Z,1}$	0.003 (0.15)		
$\delta_{Y,Z,2}$	0.043 (1.73)		
	Mean spillovers from X to Y		
$\delta_{Y,X,1}$	0.107 (1.66)		
$\delta_{Y,X,2}$	0.119 (1.839)		
μ_Z		−0.007* (−2.00)	
$\delta_{Z,Z,1}$		−0.40* (−8.50)	
$\delta_{Z,Z,2}$		−0.282* (5.96)	
		Mean spillovers from Y to Z	
$\delta_{Z,Y,1}$		−0.17* (−1.88)	
$\delta_{Z,Y,2}$		**−0.264* (−2.86)**	
		Mean spillovers from X to Z	
$\delta_{Z,X,1}$		**−0.264* (−2.17)**	
$\delta_{Z,X,2}$		−0.01 (−0.08)	
μ_X			−0.000 (−0.23)
$\delta_{X,X,1}$			0.37* (7.58)
$\delta_{X,X,2}$			−0.09 (1.90)
			Mean spillovers from Y to X
$\delta_{X,Y,1}$			−0.01 (−0.40)
$\delta_{X,Y,2}$			0.008 (0.21)
			Mean spillovers from Z to X
$\delta_{X,Z,1}$			0.016 (0.83)
$\delta_{X,Z,2}$			0.01 (0.53)
Log likelihood			2,444.8

*Statistical significance at the 5% level. Bold numbers indicate statistically significant spillovers from another market.

modeling of the "true" dynamic spillover linkages between these variables should "clean" these spillovers prior to measuring the "net" dynamic correlation effects.

The estimation of the mean equation for the returns differential reveals that there exist statistically significant spillovers from net flows at both lags, as $\delta_{Z,Y,1}$ and $\delta_{Z,Y,2}$ are strongly statistically significant. The spillover effect is negative suggesting that when the net purchase of U.K. stock is higher than the net purchase of U.S. stock if the U.K. stock return is lower than the U.S. return over the next two subsequent months. This result establishes a dynamic link between portfolio rebalancing and subsequent stock returns of these constituents and highlights the possible existence of a trading rule according to which portfolios are dynamically adjusted in a relatively short-run time horizon (1–2 months) entailing changes in stock returns. In terms of the dynamic effect of exchange rate returns, coefficient $\delta_{Z,X,1}$, capturing the effect of exchange rate returns upon returns differential at lag 1 is statistically significant and negative. This suggests that an appreciation of the pound yields a negative returns differential, that is, an increase in U.S. returns relative to the U.K. stock returns. This result is in line with the positive dynamic effect from exchange rate returns to net flows: An appreciation of the pound leads U.K. investors to putting relatively more emphasis on buying U.S. stocks which leads to higher returns.

Finally, the estimation of the mean equation of exchange rate returns reveals that the two autoregressive coefficients are both significant, but no spillover coefficient is significant. Thus, exchange rate returns appear not to be recipients of dynamic effects from net flows and the returns differential, but they are exporters of mean spillovers to these two variables. The fact that there is no statistically significant effect, either from the returns differential to exchange rate returns or from net equity flows to exchange rate returns, is in contrast to the implications of the theoretical model of Hau and Rey (2006).

Overall, we conclude that the conditional means of net flows and returns differentials are both importers and exporters of spillovers whilst exchange rate returns are only exporters. Uncovering and allowing for these spillovers is important in terms of correctly measuring the pair-wise linkages of these variables reflected in their covariances.

TABLE 3 VAR(2)-GARCH(1,1)-t-DCC(1,1) model with mean and variance spillovers

	Dependent variable: (Y = net flows)	**Dependent variable: (Z = returns differential)**	**Dependent variable: (X = exchange rate return)**
Panel A: Conditional mean equations parameters			
μ_Y	−0.003* (−5.96)		
$\delta_{Y,Y,1}$	0.398* (9.85)		
$\delta_{Y,Y,2}$	0.192* (5.08)		
	Mean spillovers from Z to Y		
$\delta_{Y,Z,1}$	**0.011* (3.07)**		
$\delta_{Y,Z,2}$	**0.045* (6.732)**		
	Mean spillovers from X to Y		
$\delta_{Y,X,1}$	**−0.035* (−4.01)**		
$\delta_{Y,X,2}$	−0.006 (−0.47)		
μ_Z		−0.007* (−3.18)	
$\delta_{Z,Z,1}$		−0.435 (−12.12)	
$\delta_{Z,Z,2}$		−0.26 (−6.69)	
		Mean spillovers from Y to Z	
$\delta_{Z,Y,1}$		**−0.18* (−3.38)**	
$\delta_{Z,Y,2}$		**−0.27* (−4.13)**	
		Mean spillovers from X to Z	
$\delta_{Z,X,1}$		**−0.233* (−2.63)**	
$\delta_{Z,X,2}$		0.033 (0.40)	
μ_X			−0.000 (−0.74)
$\delta_{X,X,1}$			0.26* (8.42)
$\delta_{X,X,2}$			−0.10* (2.83)
			Mean spillovers from Y to X
$\delta_{X,Y,1}$			−0.03 (−1.06)
$\delta_{X,Y,2}$			0.004 (−0.17)
			Mean spillovers from Z to X
$\delta_{X,Z,1}$			0.02 (1.40)
$\delta_{X,Z,2}$			0.004 (0.36)
Panel B: Conditional variance equations parameters			
c_Y (×1,000)	−0.01 (91.69)		
a_Y	0.062* (24.98)		
b_Y	0.814* (231.61)		
	Variance spillovers from Z and X to Y		
$a_{Y,Z}$	**−0.0188* (−7.53)**		
$a_{Y,X}$	**0.072* (31.93)**		
c_Z (×1,000)		0.1 (41.86)	
a_Z		0.077* (60.78)	
b_Z		0.876* (302.35)	
		Variance spillovers from Y and X to Z	
$a_{Z,Y}$		**0.264* (9.11)**	
$a_{Z,X}$		−0.05 (−0.68)	
c_X (×1,000)			0.04 (1.62)
a_X			0.13* (22.74)
b_X			0.86* (147.98)
			Variance spillovers from Y and Z to X
$a_{X,Y}$			−0.047 (−0.55)
$a_{X,Z}$			**0.045* (2.55)**
Panel C: Dynamic conditional correlation parameters and average correlation coefficients			
υ_1	0.0036* (5.54)		
λ_1	0.863* (10.38)		

(*Continues*)

TABLE 3 (Continued)

	Dependent variable: (*Y* = net flows)	Dependent variable: (*Z* = returns differential)	Dependent variable: (*X* = exchange rate return)
$\overline{\rho_{YZ,t}}$	−0.097* (−369.38)		
$\overline{\rho_{XZ,t}}$	−0.11* (−402.94)		
$\overline{\rho_{XY,t}}$	0.01* (32.01)		
Likelihood parameters and residuals diagnostics			
θ	11.54* (4.16)		
Log-lik	2,620.05		
LB(16)	21.47 (0.16)	18.96 (0.27)	12.14 (0.73)
LB2 (16)	3.38 (0.99)	5.28 (0.99)	12.62 (0.70)

Note. The estimated model is as follows:

$$Y_t=\mu_Y+\delta_{Y,Y,1}Y_{t-1}+\delta_{Y,Y,2}Y_{t-2}+\delta_{Y,Z,1}Z_{t-1}+\delta_{Y,Z,2}Z_{t-2}+\delta_{Y,X,1}X_{t-1}+\delta_{Y,X,2}X_{t-2}+\varepsilon_{Y,t}$$
$$Z_t=\mu_Y+\delta_{Z,Z,1}Z_{t-1}+\delta_{Z,Z,2}Z_{t-2}+\delta_{Z,Y,1}Y_{t-1}+\delta_{Z,Y,2}Y_{t-2}+\delta_{Z,X,1}X_{t-1}+\delta_{Z,X,2}X_{t-2}+\varepsilon_{Z,t}$$
$$X_t=\mu_X+\delta_{X,X,1}X_{t-1}+\delta_{X,X,2}X_{t-2}+\delta_{X,Y,1}Y_{t-1}+\delta_{X,Y,2}Y_{t-2}+\delta_{X,Z,1}Z_{t-1}+\delta_{X,Z,2}Z_{t-2}+\varepsilon_{X,t},$$
$$h^2_{Y,t}=c_Y+a_Y\varepsilon^2_{Y,t-1}+b_Yh^2_{Y,t-1}+a_{Y,Z}\varepsilon^2_{Z,t-1}+a_{Y,X}\varepsilon^2_{X,t-1}h^2_{Z,t}=c_Z+a_Z\varepsilon^2_{Z,t-1}+b_Zh^2_{Z,t-1}+a_{Z,Y}\varepsilon^2_{Y,t-1}+a_{Z,X}\varepsilon^2_{X,t-1}$$
$$h^2_{X,t}=c_X+a_X\varepsilon^2_{X,t-1}+b_Xh^2_{X,t-1}+a_{X,Z}\varepsilon^2_{Z,t-1}+a_{X,Y}\varepsilon^2_{Y,t-1}$$
$$\rho_{12,t}=q_{12,t}/\sqrt{q_{11,t}q_{22,t}}$$
$$Q_t=(1-\upsilon_1-\lambda_1)\overline{Q}+\upsilon_1\left(\varepsilon_{t-1}\varepsilon'_{t-1}\right)+\lambda_1Q_{t-1}$$

Note. $\overline{\rho_{12,t}}$ is the mean value of the conditional correlation coefficient.

Note. The t-distribution is assumed with θ degrees of freedom. Estimation was based on Ling and McAlleer (2003) regarding the asymptotic theory for the quasi maximum likelihood estimator (QMLE) for the vector trivariate GARCH model.

Note. Robust t-statistics, based on Bollerslev and Wooldridge (1992), are reported in the parentheses next to the estimated parameter values.

*Statistical significance at the 5% level. Bold numbers indicate statistically significant spillovers from another market.

Note. LB(16) stands for the Ljung-Box statistic of the 16th order for the standardized residuals. LB-SQ(16) is the LB statistic applied to the squared residuals. In squared brackets are *p* values for the LB statistic.

Having filtered away spillovers, the time-varying conditional covariances to be obtained from this model will be free of dependencies. In other words, the existence of spillover justifies the use of the trivariate VAR approach, as it removes these cross-variable effects.

4.2.2 | Volatility clustering, volatility spillovers, and time-varying correlations

Turning to the conditional variance equations, it can be seen that the GARCH parameters are statistically significant in all three equations, highlighting the existence of volatility clustering for all three variables. Volatility persistence, which is the sum (a_Y+b_Y), (a_Z+b_Z), and (a_X+b_X) for net flows, returns differential, and exchange rate changes, respectively, is relatively high and takes the values of 0.876, 0.953, and 0.99, respectively. In all cases, volatility persistence is less than 1 (Figure 1).

The important issue in conditional variance estimation is the existence of volatility spillovers. Spillovers in the variance of net flows from returns differential and from exchange rates returns are denoted by $a_{Y,Z}$ and $a_{Y,X}$, respectively. These coefficients are both strongly significant, thereby highlighting the existence of spillovers into the variance of net flows. Failure to control for these spillovers may entail in erroneously high correlations between net flows and returns differential and between net flows and exchange rate changes. The present approach appropriately controls for such spillovers, and the remaining correlation is a "true" correlation. In line with the above observation, the variance of returns differential appears to be dynamically affected by the variance of net flows, as indicated by the strong statistical significance of $a_{Z,Y}$. Finally, exchange rate returns are not recipients of any volatility effects either from net flows or from the returns differential, a conclusion in line with the lack of mean spillovers documented above. The exchange rate between the pound and the U.S. $ appears to be unaffected both in the conditional mean and in the conditional variance by the net flows from the United Kingdom to the United States for stock portfolios and the stock markets.

Furthermore, the two parameters of the DCC representation, υ_1 and λ_1, are both statistically significant at the 5% level. Also reported in Table 2 is the average correlation coefficient for each of the three variable-pairs. According to Lee (2006), these average correlation coefficients reflect *unconditional* correlations. The average correlation coefficient for the net flows—returns differential pair is −0.097 and statistically significant. The average correlation for the net flows—exchange rate changes is 0.01, also statistically significant. This is much lower than the value found by Hau and Rey (2006), which is 0.0775 for the period 1980–2001. Finally, the correlation coefficient for the returns differential—exchange rate changes is −0.11 and significantly different from 0. Again, this value is lower than that found by Hau and Rey (2006) for the period 1980–2001, which was −0.1187.

In terms of additional estimation output, Table 3 also reports the parameter θ capturing the shape of the distribution. This is 11.54, which is also statistically significant, and justifies that the adoption of the t-distribution. Finally,

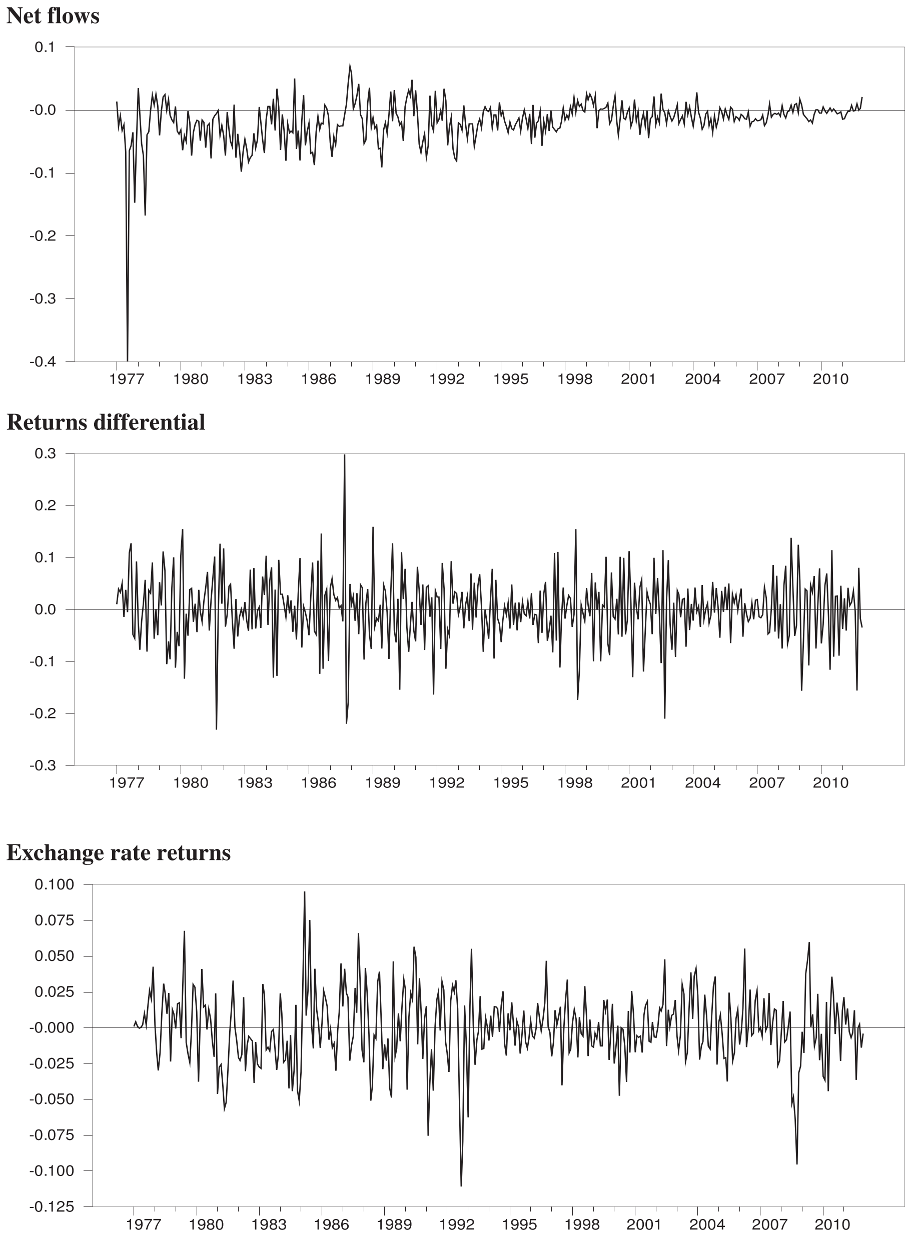

FIGURE 1 Net flows, returns differential, and exchange rate returns

we conducted numerous diagnostic tests for the estimated standardized residuals, on the basis of the Ljung-Box statistic. These tests were applied to the standardized and squared standardized residuals, trying to assess if there is evidence of remaining linear and nonlinear dependencies of higher (16th) order.[10] The results suggest that there is no evidence whatsoever of such dependencies, supporting the specification of the trivariate VAR(2)-t-GARCH(1,1)-DCC(1,1) model and the reliability of the obtained dynamic covariances.[11]

Figure 2 presents the DCCs for the three pairs of variables, namely, for the returns differential—exchange rate returns pair, the net flows—returns differential pair, and for the net flows—exchange rate returns pair. The dynamic correlations for the first pair are negative throughout the period, in line with both the theoretical and empirical findings of Hau and Rey (2006). This finding is in contrast to the conventional conjecture that a strong equity market and a strong currency come together. These authors found a monthly correlation for the U.S.–U.K. pair for the period 1980–2001, which is equal to −0.1187, very close to the average correlation of −0.11 that we have found for the period 1977–2011. Hau and Rey (2006) have argued that, this empirical evidence is compatible with the existence of incomplete foreign exchange risk trading or with a competitiveness effect of exporting firms.

For the second pair, the corresponding graph reveals that the conditional correlation varies considerably and takes values ranging from −0.07 to −0.11 approximately. Thus, for the whole period, the correlation was negative. The negative association between U.K. net equity flows and the concurrent differential between U.K. and U.S. stock returns is consistent with the conjecture by Brennan and Cao (1997)

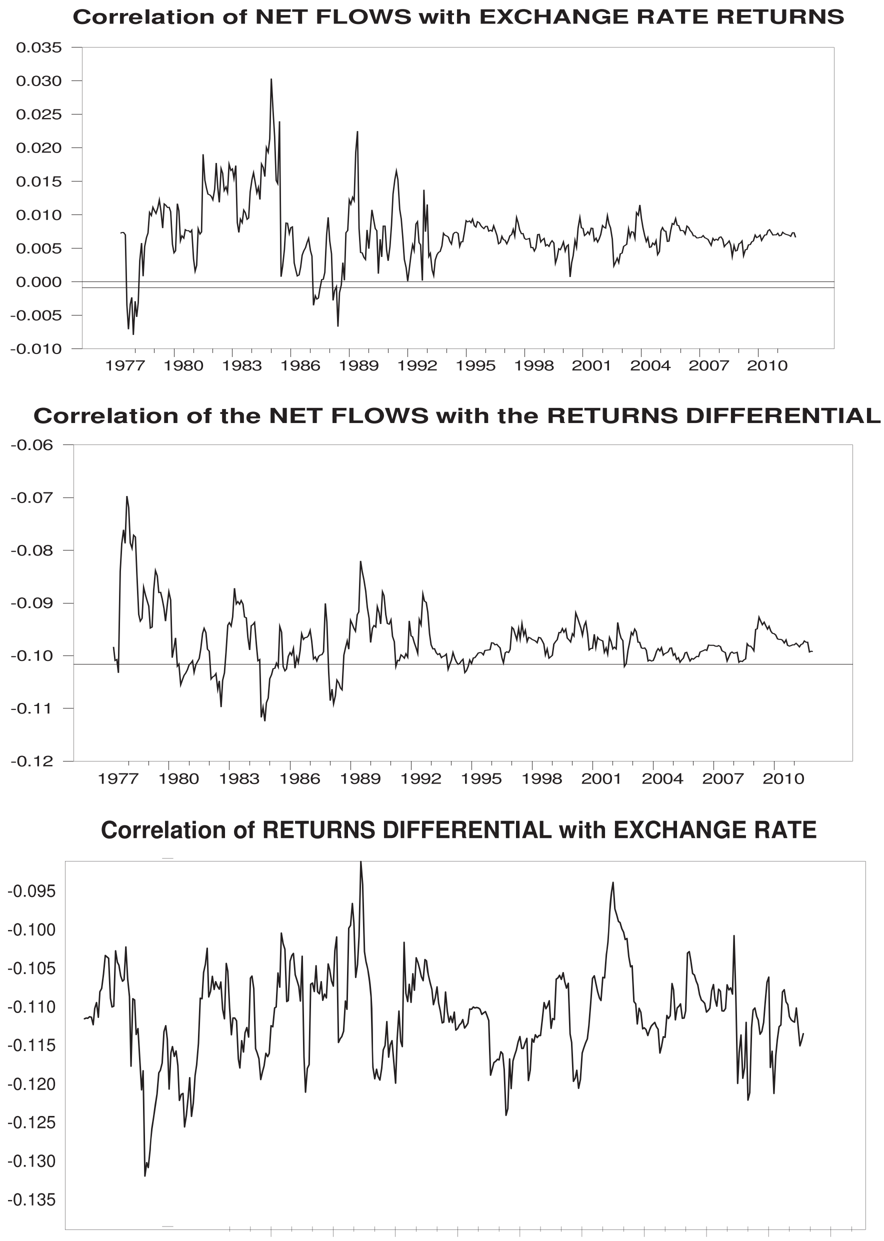

FIGURE 2 Dynamic conditional correlations

that the U.K. (U.S.) investors are more (less) informed than U.S. (U.K.) investors about the U.K. market. Finally, the correlations for the net flows—exchange rate returns pair are mainly positive, with a few exceptions in the early part of the sample period.

The dynamic correlations for the last two pairs are clearly more volatile from the start of the sample (1977) up until the early 1990s. For the net flows—returns differential pair, the correlation values range from −0.07 to −0.11 approximately, whilst for the subsequent period, the correlation values range from −0.09 to −0.10. The major conclusion that can be drawn from this graph is the distinct variation in the correlation coefficient, which is reduced from the early 1990s.

The graph portraying the correlation for the net flows—exchange rate changes pair reveals a similar picture. The correlation values range from 0.03 to −0.007 approximately, thereby suggesting that this correlation may take both negative and positive values. Remarkably, this range is observed over the period from 1977 up to the early 1990s. From the early 1990s, the variability of correlation is highly reduced with correlation taking values from 0.00 to 0.01, suggesting that net flows and currency markets became more independent. This interpretation could be justified on the basis of two facts. First, the start of this period coincides with timing of the exit of the pound from the exchange rate mechanism (ERM) of the European Monetary System. We conjecture that the reduction of "correlation uncertainty" suggests that equity market and currency market participants were rather in favor of the removal of exchange rate management (bands) constraints due to the participation of the pound into the ERM. Second, any exchange rate risk faced by market participants was hedged using currency derivatives. Indeed, as illustrated in the 2013 Triennial Survey of Foreign Exchange Markets of the Bank of International Settlements, the use of currency derivatives in the post-ERM has significantly increased suggesting that investors increased their interest in hedging currency risks (Schrimpf & Rime, 2013).

5 | CONCLUSIONS

The paper has explored the effects of equity flows between U.S. and U.K. investors upon equity and exchange rate returns within a unified empirical framework on the basis of a trivariate VAR system, which incorporates mean and volatility spillovers and allows for DCCs. Our findings extend Hau and Rey (2004, 2006) in several ways. First, we reveal strong evidence that U.K. investors rebalance their portfolios by engaging in a positive feedback trading known in the literature as trend chasing. Positive feedback trading behavior suggests that an increase in this month's returns differential leads to an increase in net flows over the next 2 months. Second, we document strong dynamic effects from net flows to equity returns, illustrating a trading rule that portfolios are dynamically adjusted over a short-run (1–2 months) horizon influencing stock returns. Third, there is evidence of volatility spillovers across equity returns, exchange rate returns, and equity flows.

Overall, our empirical results are indicative of the effects that increased capital mobility, observed in recent years, has on capital flows and exchange rate movements. Following the case of U.S. and U.K. markets, we observe that as net purchases of cross-border equities follow a dynamic path of correlations, their effect on nominal exchange rates is becoming increasingly important. Thus, if monetary policy makers respond explicitly to deviations of asset prices from their steady-state or fundamental levels, as part of their pursuit for inflation and output gap stability, particular attention should be paid in equity flows as a determinant of exchange rate movements. Last, our results carry implications for the important issue of explaining equity returns and exchange rates. In recent years, a number of studies have shown that investors' private information plays a central role in determining exchange rates or capital flows. Our findings extend this conjecture by demonstrating that private information relevant for capital movements is connected to the stock market and that this information generates dynamic correlations.

NOTES

[1] Ling and McAller (2003) showed that the quasi maximum likelihood estimator is consistent.

[2] The TIC data is downloaded from www.treasury.gov/tic

[3] Warnock (2002) provide a thorough discussion of these data. The TIC data records transactions based on the residency of the seller and of the buyer.

[4] Recent contributions which refer to TIC data include Caporale et al. (2015), Bertaut and Judson (2014), Kodongo and Ojah (2012), and Chaban (2009).

[5] We have also considered another approach to normalization, based on the average flows over the previous 12 months, as suggested by Brennan and Cao (1997), and Hau and Rey (2006). Both methods produce qualitatively similar results, and we only report those based on the total market values.

[6] Another reason for considering monthly data is based on the findings by Froot et al. (2001) and Froot and Ramadorai (2005) that the impact of equity flows on exchange rates peaks at horizons of about a month. See also Kanas (2008)

[7] A lag length of 1 failed to yield residuals free from remaining linearities in all 3 mean equations.

[8] Hypothesis 1 in Hau and Rey (2004) ['*H1*'] refers to the relation between foreign equity market changes relative to home equity market and portfolio rebalancing. In particular, foreign equity market appreciations relative to the home equity market induce a portfolio rebalancing effect in which the home investor reduces his/her foreign equity holdings in order to reduce exchange rate risk exposure. This effect results in foreign equity outflows and a dollar appreciation (Hau & Rey, 2004, page 127).

[9] As discussed in Hau and Rey (2004, 2006), in a world in which all exchange rate risk is perfectly hedged, the global investor holds the world equity market and any increase in the value of the foreign equity does not trigger portfolio rebalancing. Under imperfect risk trading, exchange rate exposure reduces the benefit of foreign investment.

[10] These tests were also applied to the cross- and squared cross-residuals, trying to assess if there is evidence of remaining linear and nonlinear dependencies of higher (16th) order. The results, not reported here to keep this Table manageable, indicated absence of any remaining linearities and nonlinearities.

[11] To ensure that the obtained correlations do not contain any interest rate effects, we re-estimated the VAR-GARCH-DCC model with the interest rate differential being treated as an exogenous variable in both the conditional mean and the conditional variance. The justification of treating this variable as an exogenous one is twofold. First, a 4-variable (if the interest rate differential was endogenous) system could not be estimated in terms of the maximization algorithm achieving convergence. Second, there would be strong correlation with the exchange rate changes, on the basis of the interest rate parity. The obtained results are very similar qualitatively with those reported here, possibly reflecting the fact that the interest rate differential and exchange rate changes carry similar information. See Warnock and Warnock (2009) for an analysis of the effects of interest rates on capital flows. We report the results of the model without the interest rate differential in order to keep the number of parameters and the size of Table 3 manageable.

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